

MPH Dissertation

Impactibility modelling: A literature review and proof of concept using multi-state modelling



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Declaration

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Abstract

The sustainability pressures faced by the health systems today will not be the same in the future. To ensure the long-term viability of Universal Health Care provision, agile solutions are being designed to navigate the dynamic problem of optimising health under constraints. Within the UK, population health management is being researched and applied. Impactibility modelling is a new development in this area which seeks the greatest increase in population health, patient experience, and reduction in health inequalities for the cost incurred.

It is important to develop and apply impactibility modelling as an agile solution, so that it may be successful in accommodating the changing nature of the optimisation problem. This dissertation provides insights in that direction at this early stage of IM development.

A literature review is conducted to understand the development of impactibility modelling so far and create practical recommendations for its development and application in the UK. These recommendations are distilled into an ethos of IM including awareness, clarity, collaboration, preparedness and working across a wider health system.

A proof of concept model shows how some of these recommendations can be applied in practice, namely clarity and awareness. Through a case study of Type 2 Diabetes Mellitus, the usefulness of multi-state modelling for the purpose of impactibility modelling is explored.

Lay Summary

There are pressures on the National Health Services ('NHS') in the UK which mean it may not always be available to us as it is today. These pressures drive people to seek creative solutions that improve health, make patients more satisfied, reduce health inequalities in society and try to lower the costs of doing so. Impactibility modelling is a new idea for a creative solution that will try to direct NHS resources in an effective and efficient way to help navigate those pressures so the NHS can continue well into the future.

This dissertation provides a summary of what has been thought about so far on this idea. It also makes recommendations to those working to develop this new idea further. An example of how some of these recommendations could be carried out in practice is provided. This example looks at health data to try to understand why some people with Type 2 Diabetes are able to control their weight and blood sugar levels better than others.

Acknowledgements

A regular practice of gratitude has the potential to enhance wellbeing (2) . With this in mind, the following have been acknowledged regularly over the course of the MPH and dissertation for their patience, support and navigation during my endeavours.

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List of Abbreviations and key terms

Abbreviations are provided, as ('___'), after the text is first introduced. A list of abbreviations is provided for reference below

ACSC.....	Ambulatory Care Sensitive Conditions
BMI.....	Body Mass Index
HbA1C.	Haemoglobin A1c
IM.....	Impactibility Modelling
IMD.....	Index of Multiple Deprivation
ICS.....	Integrated Care Systems
KPI.....	Key Performance Indicator
LHS	Learning Health System
MSM.....	Multi-state Model(s) or Modelling
NHS.....	National Health System
PHM	Population Health Management
PM.....	Predictive Modelling
QOF.....	Quality and Outcomes Framework
ROI.....	Return on Investment
RS.....	Risk Stratification
SCI.....	Scottish Care Information
STP.....	Sustainability and Transformation Partnerships
T2DM.....	Type 2 Diabetes Mellitus
UK.....	United Kingdom
US.....	United States of America
UHC.....	Universal Health Coverage

Key terms are introduced in the text and followed by a key term box.

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Chapter 1 Introduction

Universal Healthcare Coverage is established or is being established in many countries to protect people from the hardships of poor health and ensure long-term economic development (3). Health systems that deliver Universal Healthcare Coverage take many forms globally. In the United Kingdom ('UK'), the National Health System ('NHS') was established in 1948 to deliver society wide affordable medical treatment and has continued to be predominately publicly funded (4). The systems in Western societies, including the NHS, are experiencing increasing demands to deliver services and at the same time, the ability to supply services is increasingly challenging. These pressures create sustainability concerns for health systems and without change the problem is expected to worsen (4, 5).

This has motivated efforts to reimagine health systems by adopting an 'Integrated Care' approach that aims to deliver health services more holistically (4); increasing the ability of the health system to supply care more efficiently (4, 6-8). Now attention has turned to Population Health Management to deliver further improvements in health system sustainability by reducing the demand for care. Population health management seeks improvement in population health status and patient experience, while reducing health inequalities and the associated costs. This approach shifts attention from simply delivering care to preventing the requirement for care in the first place, as seen in public health. It does so by targeting intervention on those at risk of adverse health events.

It may be possible to improve the results of targeted interventions further by using Impactibility Modelling. This requires identifying those in a population most likely to be impacted positively by a particular intervention. This approach has potential to further improve health system sustainability.

This dissertation explores Impactibility Modelling and its potential contribution to Population Health Management. A literature review summarises the current state of Impactibility Modelling development. Recommendations for the development and application of Impactibility Modelling in practice follow. A proof of concept model illustrates how recommendations could be applied in practice and explores the usefulness of multi-state models to assess impactibility. Through these recommendations and proof of concept, this dissertation provides direction forward in the next steps of IM development at a time when it is just being created.

This dissertation has nine chapters. Chapter 2 provides background information, the structure used to review the literature and the aims of the dissertation. Chapter 2 to Chapter 3 cover the literature review, providing a wider appreciation of Impactibility Modelling and

conclude with recommendations. Chapter 4 to Chapter 7 cover the proof of concept, showing how the recommendations of clarity and awareness could be applied in practice and explores the usefulness of multi-state modelling. Chapter 8 discusses how this proof of concept contributes to the development of Impactibility Modelling and Chapter 9 concludes.

Chapter 2 Background

Shortly after the creation of the NHS there were sustainability pressures which saw adaptations to how the health system operated including the privatisation of dental and optical services (9). Today sustainability pressures to systems that contribute to health are present in varying nature across the world. Western health and social care systems, including the NHS in the UK, face demand-side pressures from demographic and epidemiological causes, including population ageing, obesity trends and increased prevalence of chronic disease (4, 5, 10, 11). In addition, supply-side political and financial pressures occur, including increasing public and patient expectations, medical advances, human resource skills shortages and reduced budgets (4, 5, 10, 11). These pressures are the problems now but may not be the problems faced in the future. In general, the problem is one of optimisation; to optimise health under constraints.

To match the dynamic nature of the problem, an agile solution is required. The following sections provide, in general terms, a way to view the problem and frame the solution. This provides an appreciation of the wider context for Impactibility Modelling ('IM') that influence its objectives. The application of agile solutions in the UK is discussed and the motivation behind IM as a topic.

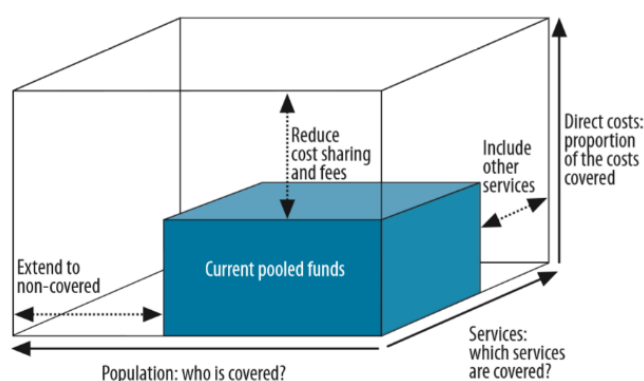
2.1 A dynamic problem: To optimise health under constraints

Optimising health under constraints can be viewed within the health and social care system and within a wider system that determines health.

2.1.1 Within the health and social care system

When an individual requires an intervention and is within the health or social care system, the Universal Healthcare Coverage ('UHC') Cube (3) and Institute of Medicine's 6 quality of care domains (12) are frameworks for optimisation problems in health.

The objective of the UHC Cube is to increase health coverage by increasing the number in society covered, increase the services offered and reduce the costs borne by the user, as shown in Figure 1.

Figure 1: WHO UHC Cube

Sourced from World Health Organisation (3)(p.13)

The dimensions of the cube could be maximised by spending more however, with limited health-economy resources, this is not feasible in the short-term. Alternatively, the dimensions could be maximised by diluting quality. Quality in delivering health services is key and can be considered in 6 domains, care ought to be: safe, effective, patient-centred, timely, efficient and equitable (12). To retain quality under resource constraints is a continuous challenge which requires ongoing monitoring and evaluation(13).

2.1.2 Within a wider health system

Before individuals need care, multiple systems work to maintain and improve health. This wider system that determines health is also where causes of ill-health mostly lie (14). This wider health system (see Key Term 1) is relevant to public health and examples of wider determinants of health are shown in Figure 2 (15).

Key Term 1: Wider health system

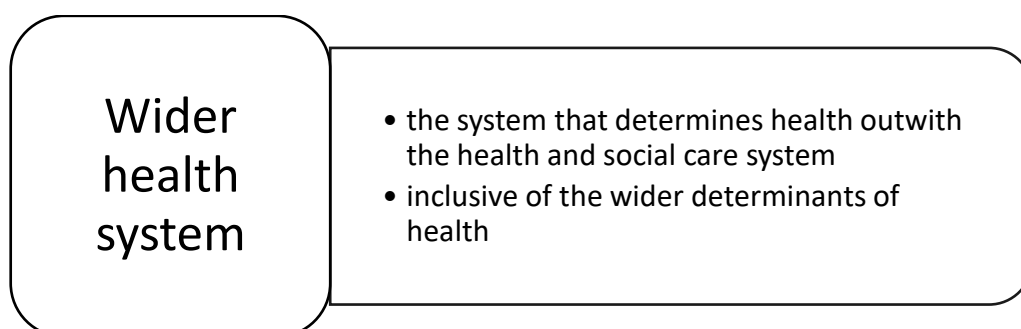


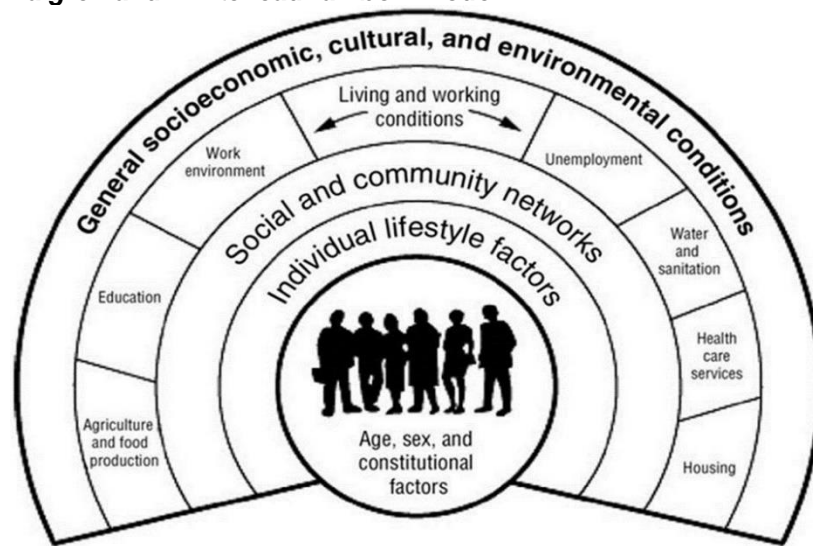
Figure 2: Dhalgren and Whitehead rainbow model

Image sourced from Public Health England (15)

The Institute for Healthcare Improvement's Triple Aim refers to the simultaneous objective of "improving patient experience (including quality and satisfaction)[,] improving the health of populations[,].and reducing the per capita cost of achieving health"(14), as shown in Figure 3. This framework can be used to view the optimisation problem across both the health and social care system and the wider health system (13, 14, 16). In the UK, a fourth aim of reducing health inequalities has been adopted (10).

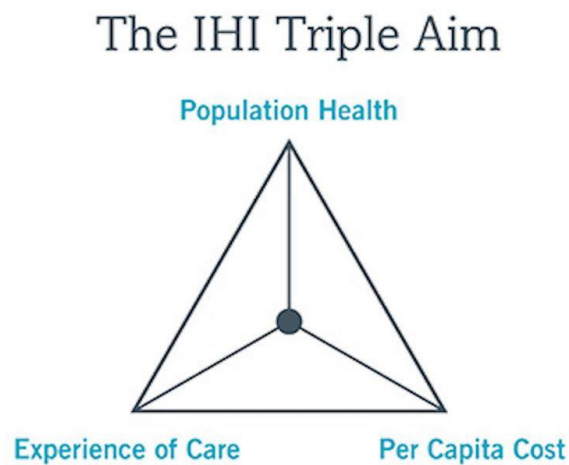
Figure 3: The IHI Triple Aim

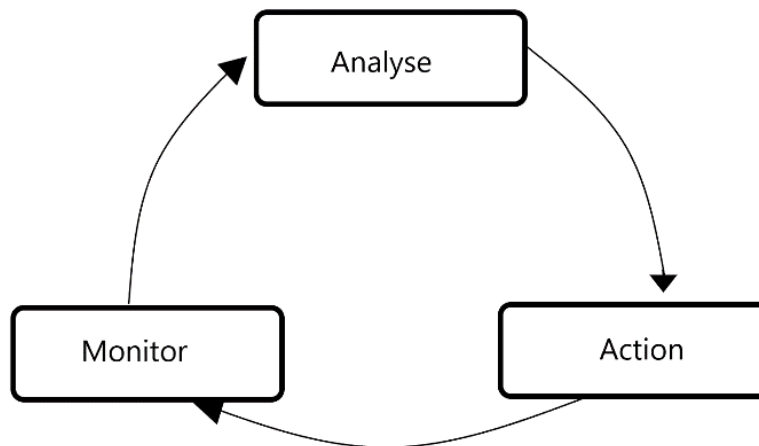
Image sourced from the Institute of Healthcare Improvement (17)

2.2 An agile solution: A control cycle

The nature of the optimisation problem varies by local context, over time and with the population. The solution must therefore adapt, requiring ongoing tailoring to suit both the local health and care system and the wider health system.

A control cycle is a generic systematic framework to develop an agile solution within (18). The process is cyclical and involves analysing the problem, developing and implementing a solution, then monitoring it (19), as shown in Figure 4, before starting again.

Figure 4: A control cycle



Based on control cycle frameworks from Moen (18)

This framework is well suited to dynamic problems such as optimising health under constraints and where a solution is not yet known but can be developed iteratively based on learnings from the process.

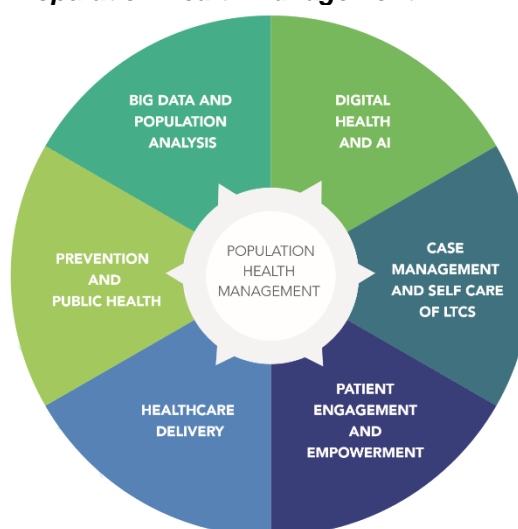
2.2.1 Population health management

PHM is a growing area of research and practice that seeks better health outcomes and distribution of outcomes using a control cycle (20). PHM seeks to “estimate[e]..the cross-sectoral cost-effectiveness of different types and combinations of investments for producing health” (21)(p.381). It seeks to optimise health as delivered across both the health and social care system and the wider health system (13).

PHM is a wide field as shown in Figure 5. Fundamental to PHM is data analysis which aims to better understand individual and population need (public health) in order to better meet

those needs (10, 13). This understanding allows for a targeted approach to the delivery of upstream and downstream interventions¹ (10, 13).

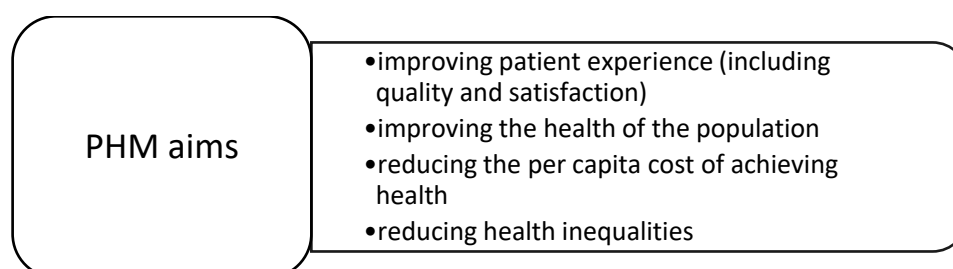
Figure 5: Dimensions of Population Health Management



Sourced from the Good Governance Institute Development and Research Report (10) (p.9)

The Triple Aim has been adopted as optimisation criteria when designing PHM solutions to optimise population health under constraints (4, 8, 10, 13, 22-27). Herein, the UK quadruple aim will be referred to as the PHM aims (see Key Term 2).

Key Term 2: Population health management aims

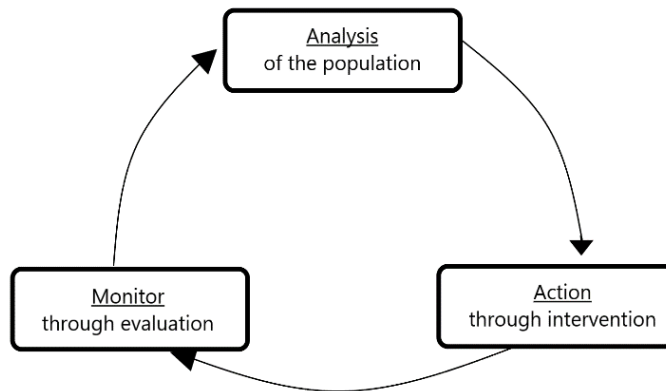


PHM systems seek to analyse population need and intervene accordingly, with the combination monitored for effectiveness in achieving the PHM aims (13), as shown in Figure 6².

¹ Upstream and downstream are used in this context to describe interventions to treat disease and interventions to treat the causes of disease.

² I have visually represented, in Figure 6, the PHM system under the control cycle process in Figure 4.

Figure 6: Analysis, action and monitor stages of Population Health Management



2.2.2 Learning health systems

When a control cycle is applied in a health system context it is known as a Learning Health System ('LHS'). PHM population analysis is an example of analysis in an LHS (28).

However, an LHS is not just analysis; it is a sociotechnical concept seen when:

science, informatics, incentives, and culture are aligned for continuous improvement and innovation, with best practices seamlessly embedded in the delivery process and new knowledge captured as an integral by-product of the delivery experience (29)

Under this control cycle, health systems develop iteratively and are responsive to the dynamic nature of the optimisation problem (30). With each complete cycle, the health system learns and continuously improves to better optimise health under constraints (28, 31).

In many countries, including the UK, the emphasis is moving away from "health systems designed to better manage chronic disease care towards systems designed to enhance population health" (10)(p.8). That is, moving away from solutions designed for today's problems to agile solutions that can adapt to the changing nature of the optimisation problem including PHM and LHS (16, 24).

2.3 UK application

The NHS model of acute episode healthcare delivery is seen as unsustainable by policymakers (10). A new model of integrated care allows for "locally appropriate proposals to improve health and care for residents"(6) providing a more seamless service to patients and investment in downstream and upstream prevention (4).

The NHS's journey toward this integrated model is progressing with Sustainability and Transformation Partnerships ('STP's) due to be replaced by Integrated Care Systems ('ICS') by April 2021(10). These collaborations between local NHS organisations and councils, to improve population health, plan the long-term needs of the local community (6) and take "collective responsibility for managing resources"(6). That is, optimising health under constraints across the health and social care system and the wider health system.

To further this journey, PHM is being researched and applied in the UK (8, 24, 32-35).

2.3.1 Application of Actuarial sciences

Actuarial sciences can help develop agile solutions using statistical analysis and data science to understand dynamic problems of health risks at an individual and population level along with resource allocation. In the United States of America ('US'), actuarial sciences are applied (19, 23, 36-40) and PHM case studies have passed the initial development phase (10, 41).

An interest in progressing PHM in the UK, and in applying actuarial sciences, has led to the creation of a working party. The PHM Working Party, established in 2018 by the Institute and Faculty of Actuaries, is a member-led working party including actuaries and NHS England professionals³ (11). The working party's initial focus is on the next development in PHM, namely IM.

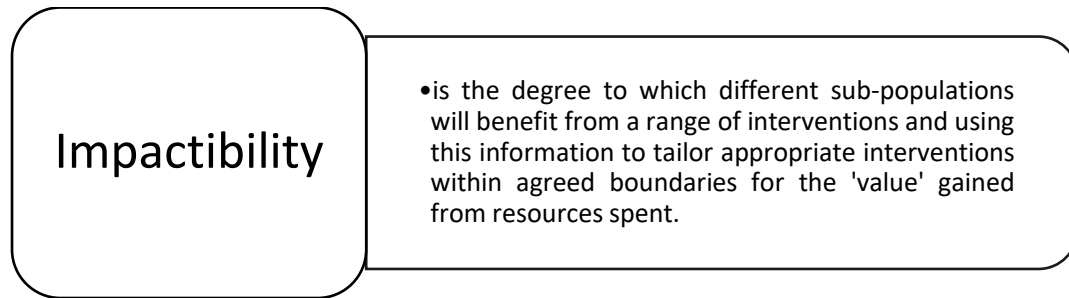
2.4 Impactability Modelling

'Impactability⁴ model' was coined by Geraint Lewis (25), Chief Data Officer at NHS England (42). A working definition was established in 2019 by the working party in collaboration with Lewis (see Key Term 3). This definition reflects the desire to optimise health under constraints.

³ More details on the Working Party including membership is provided in Appendix 2.

⁴ There is debate over if the term should be spelt 'impactability' or 'impactibility' however, following Lewis' publication in 2010, 'impactibility' has been adopted in the proceeding literature.

Key Term 3: Impactibility



Sourced from PHM working party (43)

2.5 Dissertation aims

This dissertation will explore IM as a new development to PHM and provides direction forward in that development through a literature review and proof of concept.

A literature review summarises the current state of IM's development. This is followed by practical recommendations for IM's development and application in the UK as part of the agile solution required to suit the dynamic problem of optimising health under constraints.

A proof of concept model illustrates how recommendations could be applied in practice and establish the usefulness of multi-state modelling for IM.

Chapter 3 Literature Search

3.1 Aims and objective of literature search

An agile solution can accommodate the dynamic problem of optimising health under constraints. Exploring IM as an agile solution may better allow for the structural changes considered necessary for the sustainability of the UK health system (4, 5).

To effectively explore IM, this literature search aims to:

- establish clarity in the objective of IM; and
- clearly establishes how IM fits within the control cycle framework.

The objective of this literature search is to summarise the current state of IM development and to create recommendations for the development and application of IM in practice. This has not yet been provided in the literature and is considered useful at this time when IM is just being created.

3.2 Search strategy

IM a relatively new development so a pragmatic approach has been taken to locate recent and relevant sources limited to those concerning ‘impactibility’.

A forward and backward citation search was undertaken from the working party seed papers on IM (25, 44). All references in these papers were checked for relevance in the backward citation search. A forward citation search captured current literature using Google Scholar to source citations of the seed papers as of 1 June 2019.

The term “impactibility” was searched using Google Scholar⁵ on 1 June 2019 with publication years limited 2010 to 2019 to ensure all literature since Lewis’ paper (25) was captured.

To broaden the search, materials using alternative terminology for the concept of impactibility were considered. This was not exhaustive but allowed for a wider contextual understanding of impactibility as a concept. Topics concerned with optimising health under resource constraints seemed appropriate, including priority setting and rationing (45), triage and case-finding(46), and precision medicine(47)⁶.

⁵ Medline, Embase, Web of Science, and Scopus were search but Google Scholar was the most fruitful.

⁶ More detail is provided in Appendix 4

3.3 Search summary and process

A representation of the literature search is provided in Figure 7.

Figure 7: Flow diagram of literature search

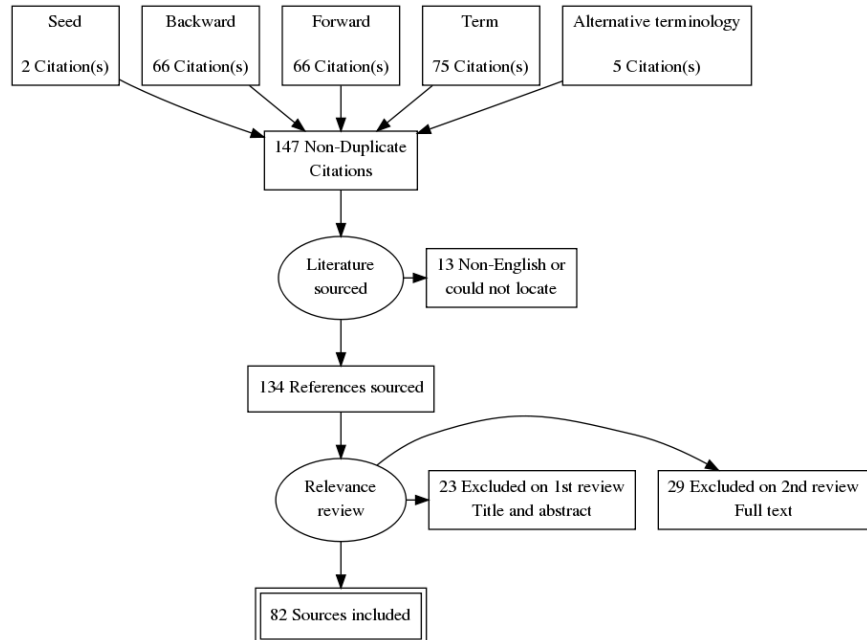


Image created using online tool Theta (48)

Literature was located, citations imported to EndNote, deduplicated and exported to Excel. After a review of the title and abstract, seemingly relevant papers were progressed to a full-text review and marked as either not relevant, low, medium or high as shown in Table 1.

Table 1: Relevance grading

Frist review: Title and abstract	Second review: Full body text
Grey – not progressed	Low – background information 37 sources
Amber – full paper review required	Medium – related to the wider context 26 sources
Green – appears to be relevant	High – directly related to 'impactibility' or IM 19 sources

Chapter 4 Literature Review

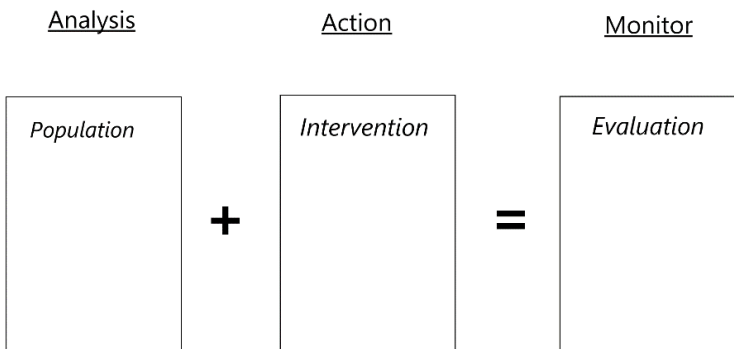
IM is part of population analysis, but in a control cycle it interacts with the intervention and the achievement of PHM aims assessed in the evaluation. All elements of PHM are therefore relevant. This review is presented using the control cycle framework presented in Chapter 2.

The PHM system is portrayed formulaically in Section 4.1. In Section 4.2 - 4.4, each element of the PHM system in Figure 8, is populated with a summary of the relevant literature. Section 4.5 summarises the literature relevant when designing IM within an LHS. Recommendations for the development and application of IM in practice are distilled into an ethos of IM which is presented to conclude.

4.1 Formulaic view of Population Health Management

PHM can be considered formulaically, as shown in Figure 8⁷. A population is analysed, provided with an appropriate intervention, and the cumulative effect evaluated against its ability to meet the PHM aims.

Figure 8: Formulaic view of Population Health Management

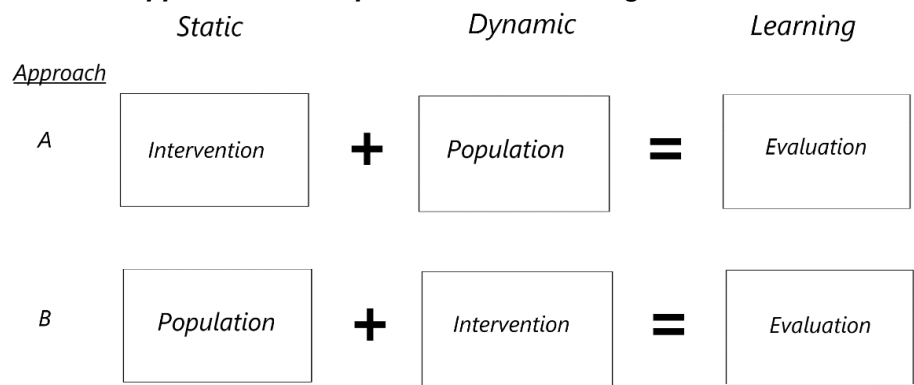


⁷ I have visually represented the PHM system under each element of the control cycle; analysis, action, and monitor.

There appear to be two possible approaches to PHM systems (49-51), referred to herein as approach A and B, represented in Figure 9⁸.

Population analysis can be used for patient selection to put forward people at-risk of an outcome, for which the intervention is intended, and for whom it is anticipated to benefit. Here the intervention does not change. A short-term return on investment ('ROI') is sought by directing selected patients to generate 'value' from resources that have been allocated. Patient selection is sometimes referred to as 'case-finding' (16, 25, 26, 50, 52-54). The literature mainly adopts approach A, where the intervention is held static (49).

Figure 9: Two approaches to Population Health Management



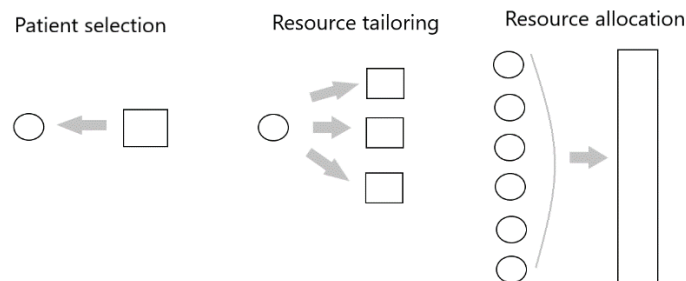
Population analysis can be undertaken to understand who is at risk of an outcome and to find which intervention would benefit that sub-population (22). Where the intervention changes to suit a given population, it is akin to precision medicine (47) which embraces the heterogeneity between individuals to find the most beneficial intervention (55). This approach is referred to as resource tailoring (49) or resource allocation (50). It seeks a long-term ROI by understanding population need and generating 'value' by allocating resources accordingly. There are fewer examples from the literature under approach B, where the intervention is dynamic (49).

Patient selection seeks to find a patient for a fixed intervention. Resource tailoring seeks to find the most suitable intervention for an individual from a menu of choices. Resource

⁸ I have visually represented the two approaches in Figure 9. The terminology of approach A and B is adopted as there was no clear alternative in the literature.

allocation seeks to set the menu of interventions available to suit the population, as shown in Figure 10⁹.

Figure 10: Patient selection, resource tailoring and resource allocation



Approach A and B to PHM can align with the strategic objective of navigating away from the acute delivery of healthcare (a static solution) toward increasing population health through collaboration of wider health system actors (an agile solution). The role IM plays within a PHM system depends on the approach adopted; altering its objectives. Under approach A, impactability criteria are chosen to allocate patients to an intervention. Under approach B, impactability criteria are chosen to allocate suitable interventions to patients.

4.2 Population analysis

In a PHM system, data analytics are leveraged in population analysis (16) to understand and predict population need (10). This predictive modelling ('PM') provides insights that allow people at risk of adverse health outcomes and people that can benefit from an intervention, or not, to be considered by clinical practitioners before the event occurs (10, 16, 25). It facilitates the proactive provision of interventions (16, 24, 25, 27) to better manage the adverse health outcome risk and so better achieve the PHM aims (16, 24, 26, 33).

PM under approach A for patient selection is similar to triage; it is an attempt to increase transparency and formalise practice for priority-setting while relying on clinical judgement (16, 46). Under approach B, PM allows population need to be understood and resources planned on forecast future need (49). It also allows policymakers to target and prioritise services specific to the local context (56) with increased transparency using insights gained from experience exhibited in local data (10).

⁹ I have visually represented this in Figure 10 where the circles represent people, the squares interventions and the arrows represent the decision made.

In this setting, PM has two elements; risk stratification ('RS') and IM. RS highlights the people at risk of an outcome such that an appropriate intervention can be allocated (7, 24-26, 49, 57). IM highlights which people may benefit from a given intervention under approach A or allows for improved resource tailoring and allocation to benefit people under approach B (25, 44, 49).

4.2.1 Risk stratification

The majority of PM so far has been RS which stratifies a population by the risk of an adverse health outcome based on historic data (11, 16, 22, 24, 25, 58, 59). Explanatory variables are established as risk factors for the event and these insights leveraged to find people susceptible to the event in the future (22, 25, 26). The objective of RS is to flag people at-risk to practitioners before an event occurs (7, 23, 25, 26, 49, 57, 59).

There is a need for high quality electronic health record data that contains the outcome of interest and explanatory variables (41, 57). Linked primary, secondary and social care data sources are useful as more factors affecting an individual's health can be appreciation and translated into action (16, 60). The data needs to be timely and of good quality to allow for appropriate actions to be taken (53).

4.2.1.1 Explanatory variables

Data items can be tested for statistically significant explanatory power over the outcome of interest (25, 59). Demographic, clinical and social explanatory factors are commonly used (7, 61, 62) but the variables may be specific to the outcome, data, time period and population (7, 63).

Commentary on how the choice of explanatory variables contribute to or detract from the achievement of PHM aims is discussed only theoretically in the literature (22, 24). For example, given the Inverse Care Law (64) selecting Index of Multiple Deprivation ('IMD') may highlight high-risk patients in lower socio-economic areas. Combined with proactive intervention, this may improve health status and reducing health inequalities in a population (25). However, how this will be measured, why it was chosen and how it is assumed to meet the PHM aims is not explicit in the literature.

4.2.1.2 Outcomes of interest

Lewis suggests that the outcome of interest for the RS model should be "undesirable to the patient, significant to the health services, preventable, and recorded in routine administrative data"(57)(p.4). More generally, the outcome of interest could be any event such that the management of that event works towards the PHM aims.

Medical outcomes and patient behaviour are less common outcomes of interest in the RS literature (23). The most common is hospital admissions, especially preventable and unplanned admissions (24, 33, 44, 57, 61-63, 65-70). This outcome is chosen explicitly to reduce costs as hospitalisation is an expensive form of care (44, 65). Although “intuitive[this is] a largely untested assumption”(8)(p.244) and the literature is silent on how this outcome contributes to the other PHM aims (65).

IM is a new development to population analysis and learnings can be leveraged from RS experience so far. There is a lack of clarity in the literature on why and how the choice of the outcome and explanatory variables achieve each of the PHM aim.

4.2.2 Impactibility modelling

IM goes beyond predicting who is at-risk, to provide insight on ‘impactibility’ i.e. “who will and who will not respond to preventive interventions”(10)(p.13). Literature specifically regarding IM primarily discusses the rationale and theoretical approaches.

4.2.2.1 The rationale

Steventon provides a strong argument and clear rationale for IM; the objective of preventing the outcome of interest is to achieve the PHM aims and RS alone, without consideration for impactibility, will not meet this objective (44). Interventions use limited resources therefore there is a need to increase the ‘value’ gained from resources spent.

The problem of optimising health under constraints is one of seeking a higher ROI; for the cost incurred the greatest improvement to population health, patient experience and reduction to health inequalities is sought, i.e. the PHM aims. The objective of IM is to contribute to the ROI through population analysis to better target the allocation of resources to population need (approach B) or target the allocation of patients to interventions (approach A) (16, 22, 24, 25).

4.2.2.2 Theoretical proposals

Theoretical approaches to IM are proposed predominately by Lewis (22, 24, 25). For the purpose of this dissertation, Table 2 categorises and summarises these; the first column shows proposals where the intervention is static, the second column where the intervention is dynamic, and proposals are then grouped by the nature of the criteria used in the model to understand impactibility.

Proposals 1 to 3 suggest impactibility criteria based on disease, patient characteristics and risk strata for patient selection, discussed in Section 4.2.3.1. Proposal 5 requires further

research to understand the drivers of impactibility to allow interventions to be appropriately tailored to create an impact, discussed in Section 4.2.3.2.

Table 2: Categories of proposed theoretical approaches to Impactibility Modelling

Approach A	Approach B
<u>Proposal 1: Disease based</u> <ul style="list-style-type: none"> Giving priority to diseases that are amenable to preventative care or Focusing on impactable conditions <p><i>Examples include</i></p> <ul style="list-style-type: none"> ➤ Analysis by disease measures ➤ Analysing resources expected for a given condition 	<u>Proposal 5: Patient characteristics based</u> <ul style="list-style-type: none"> Identifying forms of preventative care best matched to patient's characteristics <p><i>Examples include</i></p> <ul style="list-style-type: none"> ➤ propensity to engage ➤ patient activation measures ➤ propensity to complete an intervention
<u>Proposal 2: Patient characteristic based</u> <ul style="list-style-type: none"> Excluding patients least likely to respond to preventative care <p><i>Examples include</i></p> <ul style="list-style-type: none"> ➤ specific characteristics like language ➤ stable characteristics like medication adherence 	
<u>Proposal 3: Risk strata based</u> <ul style="list-style-type: none"> Exclude high-risk patients <p><i>Examples include</i></p> <ul style="list-style-type: none"> ➤ high-risk scores or rising risk scores 	
<u>Proposal 4: Service provision and utilisation</u> <ul style="list-style-type: none"> Gap analysis and weighted gap analysis <p><i>Examples include</i></p> <ul style="list-style-type: none"> ➤ variability in utilisation ➤ propensity to benefit scores 	

Table is created based on proposals found in the literature (22, 24, 25, 43, 52, 56, 71-73)

Proposal 4 based on service provision or utilisation will not be progressed here. These proposals limit the scope of resulting action to the health and social care system and do not truly assess an individual's impactibility. This is because understanding why people are not provided with required interventions provides reflection on the quality in the delivery of

services, not a reflection on the impact created by the delivery of quality services. This distinction is not clearly established in the literature¹⁰.

4.2.3 Impactibility criteria derivation

Population analysis results in the derivation of criteria to base action upon. Impactibility criteria could concern the potential to mitigate the outcome of interest, or the patients' willingness or ability to participate in an intervention (53, 74, 75).

4.2.3.1 Criteria for patient selection

Criteria for patient selection can be derived from clinical judgement, rules, or be data-driven (57, 74). Selection criteria can be inclusive or exclusive (7, 23, 25, 53). For example, an individual can be included for an intervention if at high-risk but excluded due to a lack of impactibility.

4.2.3.1.1 Clinical Judgement

Without PM, patient selection would be derived from clinical judgement as risk and impact assessments are part of daily practice (50, 53). Criteria are based on medical training, research and more subjectively, on previous patients' experience, and 'gut feelings' (50, 53, 71, 74-76).

PM can be helpful for 'case-finding' under approach A, when faced with complex multi-morbidity patients and increasing amounts of data to weigh systematically in clinical decision-making (10, 28). Currently, where patient selection is supported by RS it is supplemented for impactibility criteria outside of the model by applying clinical judgement to a shortlist of at-risk patients (16, 50, 53).

4.2.3.1.2 Rules

Criteria could be based on rules that formalise clinical judgement criteria (46). Cohen et al. provides an example of impactibility criteria derivation using disease and patient characteristics to explain impactibility, as suggested under proposal 1 and 2 (73). In this example of IM, clinicians short-listed a RS at-risk patient list and the rationale was then formalised into mainly exclusion criteria based on clinical assessment of 'ability to benefit' (73). A common clinical judgement impactibility exclusion rule removes shorter survival durations not expected to realise the benefit of the intervention (71, 73, 77).

¹⁰ Further elaboration is provided in Appendix 3.

4.2.3.1.3 *Data-driven*

Experience exhibited in routine health data can be leveraged to provide useful insight into risk (51). A threshold level of risk for patient selection can be created that strikes a balance between highlighting a sufficient number of people at-risk to have an impact on the PHM aims but not so many that action cannot be effectively implemented (22, 24, 73). This risk threshold could be leveraged as impactibility criterion (22, 24, 25, 73, 78); removing people at such high-risk that the benefit of the intervention is not expected to be realised. A worked example of proposal 3 is not available in the literature.

Alternatively, impactibility criteria can be created based directly on the experience seen in the data. There are two data-driven IM examples in the literature under proposal 1, based on disease. Stokes et al. analyses, by measures of disease, the impact of case management on cost and care utilisations data (52). Buja et al. analyses sets of multi-morbidities expected to have similar utilisation as an explanatory variable for variations in hospital admissions (56).

Patient can be included or excluded based on impactibility criteria. However, understanding the driver of risk and impact is the basis for resource tailoring.

4.2.3.2 **Criteria for resource tailoring**

IM for resource tailoring seeks to identify interventions best suited to patient characteristics (25), under proposal 5. This requires an understanding of the drivers of, not just an assessment of, risk and impactibility (79). Further secondary or primary research may be required to derive impactibility criteria (44, 49, 51, 72).

Dubard and Jackson's conducted secondary research on routine health data to identify the drivers of impactibility for patients with case management as an intervention (72).

Demographic, clinical and utilisation variables were tested as potential drivers of impactibility, defined as potential cost savings. Medical adherence was found to be explanatory and provided insight on how interventions could be adapted to better achieve the PHM aims.

There are limitations however on basing actions on insights from routine administrative data (80, 81). Data items, not collected for this purpose, may act as proxies for the underlying drivers of risk or impactibility (44). In addition, the drivers may not be present in the data (8, 79) including social factors like relationships, language barriers, isolation, living arrangements and substance use (25, 82). Actions based on uninformative impactibility

criteria may be wasteful. Therefore, primary research may be required (44, 79, 82-84)¹¹. Resource tailoring often requires further analysis of the drivers of risk and impactability to create appropriate action such as altering patient behaviour or engagement, or altering the intervention to reflect patient preferences (13, 25, 44, 75, 79, 84-89). One of the PHM aims is patient experience, including quality and satisfaction (14) and a quality of care domain is patient-centredness (12). However, this area is under-represented in the literature.

4.2.3.3 Criteria in combination

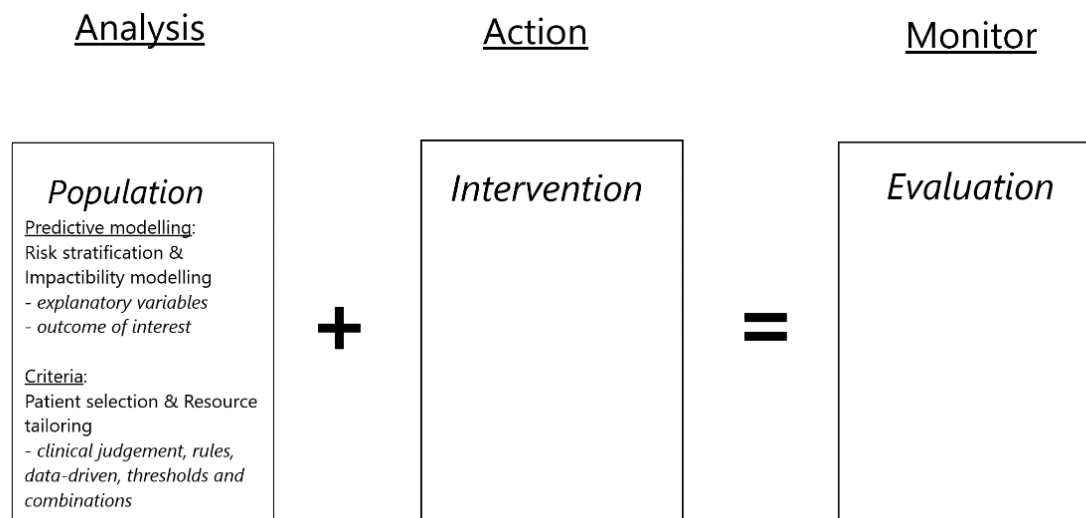
Clinical judgement is susceptible to a range of cognitive biases (24, 53, 73, 74) and is less accurate in determining current risk (24, 33) than PM. However, it is more effective at predicting future deterioration of currently low-risk patients (90). Data-driven methods can be susceptible to regression to the mean where, even without the intervention, current high-risk patients are not future high-risk patients (8, 24, 57, 70). This implies less benefit is derived from the proactive provision of an intervention to a current high-risk patient than a rising risk patient. A study showed that patients independently selected by both clinical judgement and data-driven criteria had higher risk and impactability. This, and other studies, suggests a combination of criteria derivation methods may be beneficial when designing IM (53, 74, 91).

A model is a simplification of reality and as such PM is designed to aid, not replace clinical judgements (50). A predicted list of patients must be inspected in light of the complexities that are not present in the data (8, 74, 78). When implementing PM, it is more acceptable to allow clinical judgement to interact with PM in decision-making (27, 52, 53). The usefulness of PM output for practitioners is important (53) and building in common clinical judgment criteria improves acceptability such as survival duration (8, 53). Engagement with local healthcare teams and services users when deriving criteria establishes a better understanding and acceptance of the IM objectives (27), leading to more successful implementation (44, 50).

¹¹ Primary research was not conducted for this project, so additional detail is moved to Appendix 5.

The PHM system discussed so far is summarised in Figure 11.

Figure 11: PHM summary – population analysis



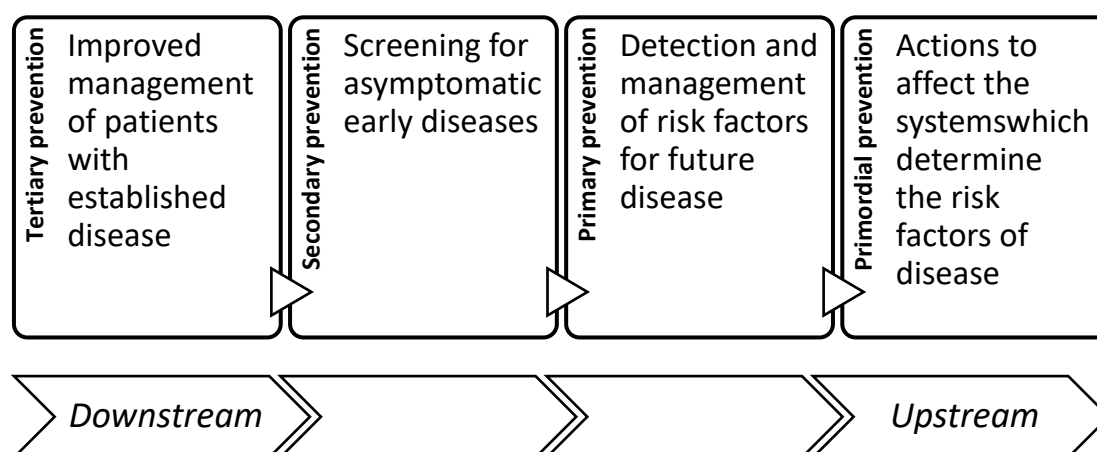
4.3 The intervention

Based on the results of the population analysis, action is taken in the form of an intervention. An intervention is considered here as any measure undertaken to prevent the adverse health outcome of interest. PHM can include interventions across both the health and social care system and the wider health system (10, 13).

4.3.1 Possible interventions: stages of prevention

Intervention can be provided at different stages of disease progression to prevent an adverse health outcome. The range of downstream to upstream interventions can be described as four prevention stages (92, 93), shown in Figure 12¹².

Figure 12: Intervention stages at each level of prevention



Based on Disease prevention: a critical toolkit (93)(p.11)

The restricted focus of the PM literature on outcomes of interest in the health and social care system (24, 44, 57, 65, 66), such as hospital admissions, appears to have restricted the intervention to tertiary prevention. This includes the improved management of patients with established disease (16, 26, 52, 94, 95). In the UK, this include case management, self-management programmes, and altering the location of care delivery (4, 8, 24, 33, 34, 96).

The literature highlights the need to consider primary prevention when discussing, at an individual level, the contributors to risk and impactability such as housing, transportation, and behavioural aspects including medication exercise, diet, and substance use (8, 25, 75, 76, 79, 97, 98). However, Stokes et al. stresses the importance of primordial prevention by

¹² Elaboration and examples of prevention stages in PHM are provided in Appendix 6.

recognising that social factors ,that drive risk and impactibility, are “multifaceted, deeply ingrained and linked to the wider social context, and therefore highly resistant to change” at an individual level (8)(p.249).

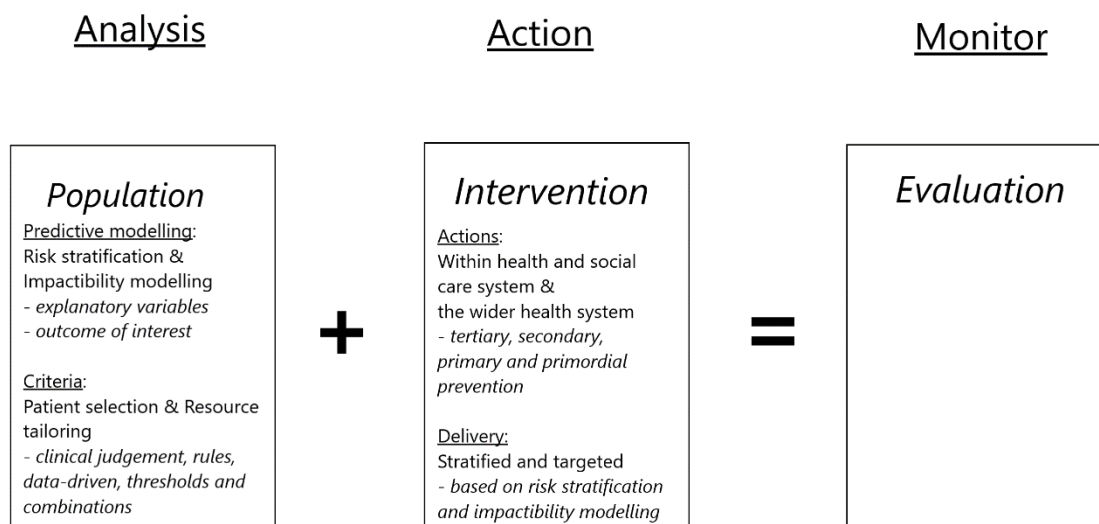
4.3.2 Delivering a stratified and targeted approach

Rose describes a population and targeted approach to prevention (99). A middle ground of a stratified approach is put forward by Lewis which sees population analysis leveraged to target preventative action; people are assigned to different interventions dependent on risk and impactibility (22, 28, 57). In Somerset and Salford, UK all population ‘risk’ levels are targeted in some respect (8); prevention is targeted at high-risk patients but also provision made for prevention to low-risk patients (67).

Therefore, impactibility criteria could be used a rationale for intervention and prevention stage choice. Those impactable by an intervention can be targeted in patient selection (22) and those less impactable could be the target of earlier prevention (8). Importantly, a lack of impactibility is not a reason not to take action and, at the least, should be the reason for reviewing the effectiveness of and seeking improvements to interventions to better achieve the PHM aims (22).

The PHM system detailed so far is summarised in Figure 13.

Figure 13: PHM summary – intervention



4.4 The evaluation

When the intention is to iteratively develop a solution within an LHS, the merit of PM may not be judged on its initial implementation. This may also limit the ability to simultaneously evaluate models in different locations (100); the model will be in different stages of development and specific to the context.

However, a plan for the evaluation is required. The literature comments on a lack of clarity in defining evaluation terms in advance and a lack of clarity in assessing PHM systems overall, against the PHM aims, and each component part for accuracy and effectiveness (27, 35).

4.4.1 Overall PHM system

The uncertainty regarding the success of PHM systems is apparent in the literature (8, 24, 44, 67, 101-104). This appears to stem from a lack of clarity and preparedness for the evaluation. When assessing the PHM system overall, the evaluation requires consideration for the terms and method.

The terms of the evaluation must be established. The literature reviewed primarily concerned reducing hospital admissions or costs for high-risk and high-cost patients (8, 24, 25, 35, 52, 56, 67, 72, 105, 106). Case management, as an intervention, can increase patient satisfaction (95) and health status but at the expense of increasing utilisation and costs (52). However, if unserved needs are met this may not be a failure overall (52, 107). PHM should enable savings that recoup its cost (22, 24, 57). However, the overall objective is to optimise population health under constraints so measuring costs alone is not sufficient to warrant success. How the design of IM proposals influence health inequalities and patient experience is commonly not commented on which makes the terms of evaluation unclear (35).

The literature is not explicit on the relative importance of each of the PHM aim however, having a clear understanding on the priority of the aims in the local context is suggested to be a contributor to successful PM implementation (8, 27, 44, 75). The first step in designing a PHM system is to understand the nature of the problem faced (44). This requires analysts and modellers to work in close collaboration with local practitioners, patients and the public representatives (44). A clear understanding of the problem faced in the local context may allow for clear evaluation metrics to be agreed in advance and defined to mirror local priority of the aims.

An evaluation method must be chosen to ensure a valid comparator group (24, 57). Evaluations must account for 'regression to the mean' (67) and supply induced demand¹³ (33, 57, 67). Lewis states that working collaboratively across NHS organisations to pool data for evaluation may be beneficial (24). However, what is gained through increased relevance to the local context when designing IM may be lost in generalisability for a pooled evaluation. A PHM system may need to be in place for some time to see an effect to the overall objective, so defining key performance indicators ('KPIs') of success in the short, medium and long term that account for variation by chance over those time periods, would be beneficial (28, 67).

4.4.2 Component parts

The PHM system has two parts for success: choosing the right people (population analysis) and providing a quality programme (the intervention) (71).

PM tools will never be fully accurate, as models are only representations of reality. There may be potential negative consequences of false positives (providing an intervention when it is not needed) and false negatives (not providing an intervention when it is needed) (24, 25). Population analysis can be evaluated on model fit to historic data and predictive accuracy (24, 25, 57, 59, 63). The well-developed RS literature can be leveraged here for IM, although the suitability of the measure will vary depending on model (57, 59)¹⁴.

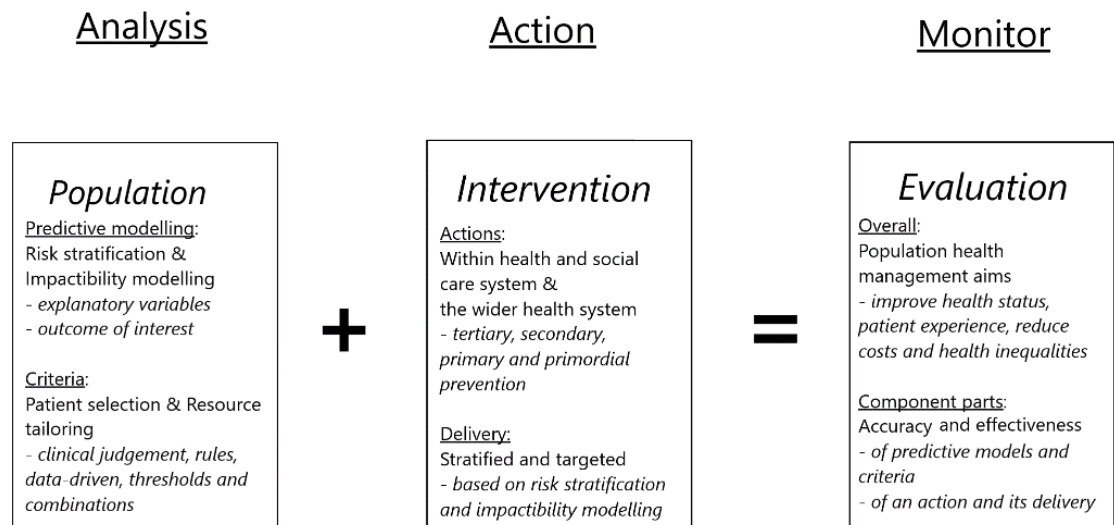
An evaluation of intervention effectiveness can be multifaceted. In an LHS, comparative effectiveness research can assess the impact created by an intervention in a population (28, 80). IM could be used to compare population effectiveness to the proposed efficacy (24, 71). This may assist decision-making on when to cease an ineffective intervention to better achieve the PHM aims (55).

¹³ Supply induced demand refers to a situation where if resources are 'freed-up' these will subsequently be used. Also known as Roemer's law; 'a hospital bed built is a hospital bed filled'.

¹⁴ Further commentary is provided in Appendix 7 on these measures.

The PHM system detailed so far is summarised in Figure 14.

Figure 14: PHM summary – evaluation

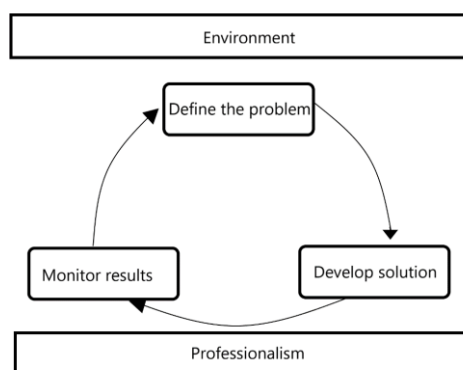


4.5 A Learning Health System control cycle

In an LHS, the continued development of IM makes it part of an agile solution (22, 24, 41). A plan should be agreed on how frequently models are run, recalibrated and rebuilt as required in the cycle (57).

The Actuarial Control Cycle, shown in Figure 15, has two additional elements, environment and professionalism, which promote the creation of an agile solution. These ensure the cycle is appropriate and responsive to the context and upholds professional standards including a duty to act in the public interest (108).

Figure 15: Actuarial control cycle



Based on an Actuarial profession publication (30)

The impact of a model's context on its design and the impact of the model on the context in which it is used must be considered as organisational aspects can undo efforts of any system (16). Uptake of IM by stakeholders is improved when clarity is provided on how IM contributes to population health (27, 41, 44). A model must be accepted and adopted within its context to be successful (16, 27). This requires training, adequate support (27) and communication and mutual learning between stakeholders (16, 41, 57).

Professionalism is required to ensure that the PHM systems work toward achieving the PHM aims in an ethical way, in line with the public interest (108). An adapted Wilson Jungner criteria ¹⁵(22, 109), shown in Table 3, or an LHS ethics framework may be relevant (110) for an IM ethical review. There are two areas of the literature, incentives and inequality concerns, that need further consideration.

Table 3: Adapted Wilson & Jungner criteria for Population Health Management

1. The event being predicted should be an important health problem.
2. There should be an accepted intervention that can mitigate the risk of the event that can be offered to high-risk patients.
3. Resources and systems should be available for timely risk stratification and provision of preventative interventions.
4. There should be sufficient time for intervention between risk stratification and occurrence of the event.
5. Sufficiently accurate predictive models for the event should be available, including risk stratification and impactibility models.
6. The predictive modelling tools should be acceptable to the population at large.
7. There should be an accepted policy about who should be offered the preventive intervention.
8. The natural history of the adverse event should be adequately understood by the organisation offering the preventative intervention.
9. The cost of stratification should be 'economically balanced', i.e. it should not be excessive relative to the cost of the program as a whole.
10. Predictive modelling stratification should be a continuous process, not just a 'once and for all' occurrence.

Adapted to table format, text sourced from Lewis (22, 24)

¹⁵ Wilson & Jungner criteria are an established means of creating a balance between the harms and benefits of screening in secondary prevention

4.5.1 Incentivisation of the control cycle

The ongoing management of the control cycle can be tied to performance objectives and financial remuneration (22, 25, 69). Reducing hospital admissions has been formally linked to financial incentives in many countries including England (44, 69).

Where KPIs are set in relation to the PM outcome of interest instead of directly to the PHM aims, the incentive to manage the control cycle may result in unintended consequences or mal-incentives (23, 107, 111). For example, reducing hospital admissions may reduce costs at the expense of health status or patient satisfaction, therefore working against the PHM aims (23). The literature shows many cases of PM designed to align with reducing hospital admissions, the basis for financial remuneration, in lieu of the PHM aims (44, 65, 67).

4.5.2 Inequality concerns

Prioritisation vs rationing in the allocation of resources is an integral difference between RS and IM and appears to be the driver of equity of access and health inequality concerns (8, 22-25, 28, 74, 75). It may be reasonable for a group at high-risk of an adverse health event to be prioritised over others, given limited resource (74), similar to triage (46, 76). However, IM suggests, under approach A, that there are some people for whom it is not worth providing an intervention to, even with a higher risk of the outcome (22, 23, 25). This implies an unjust access to healthcare (24, 28, 74). In the UK, equity in access is key to the NHS values (4, 112) and so IM used in this way may not be acceptable to the public (criteria 6 of Table 3).

A potential pitfall of IM comes from linking the impact (health outcomes) to the provision of an intervention (the access). Where those not selected by IM may be more likely to come from marginalised or disadvantaged populations characterised by health inequalities (74, 75). A spiral of unjust distribution of health outcomes could result, deepening health inequalities (22-24) and working against one of the PHM aims.

An ethnographic study in the US has shown an entangling, in terms of ROI, to the neoliberalist private approach to health care and IM (76). By striving to reduce costs, high-risk high-cost patients are targeted with interventions to reduce utilisation. This implies improved health and reduced costs, two of the PHM aims and as a by-product it reduces health inequalities by targeting those with poor health outcomes with a greater potential ROI. Therefore, it cannot be assumed that IM is in direct contradiction to a just distribution of resources nor to reducing health inequalities.

It could be suggested that withholding access to an intervention is not unjust if it is not appropriate for the individual patient (28, 113). However, failure to invest in the creation of, or

allocation of funds to, appropriate interventions could be unjust. IM under approach A may see access reduced for non-impactable people however, approach B may see resources tailored or allocated to improve impactibility. Therefore, the differentiation between approach A and B in the design of the PHM system is relevant to the acceptability of IM (24).

The potential for IM to deepening health inequality requires PHM to be designed, and the control cycle managed, to actively reduce or monitor the impact to inequalities (22, 25, 74). Using socio-economic indicators in PM and/or embedding clinical judgement may overcome inequality concerns (74). It is recommended in the literature that concerns be actively addressed to maximise the potential of IM (22, 23, 28, 67).

4.6 Literature review conclusion

In summary, the literature related to IM primarily concerns the rationale and theoretical approaches with few worked examples. There is a cautious yet optimistic view of its potential to better achieve the PHM aims and navigate health system sustainability pressures.

IM is part of population analysis, but it interacts with the intervention and the achievement of PHM aims, assessed in the evaluation. The literature does not adequately reflect this, implying that the need for IM to be developed, implemented and assessed as an agile solution may not be fully appreciated.

4.6.1 Summary of IM examples

The few IM model found develop different proposal using different impactibility criteria. The predictive accuracy is not comparable and the PHM systems are too young to assess the contribution to the PHM aims. There are fewer developments under approach B and none yet for proposal 3. The model used varies which may indicate that IM will develop as a selection of models in lieu of a single 'best' model type. The models have developed in different locations showing the commonality of the problem, to optimise health under constraints, but the variation in explanatory variables and outcomes of interests show its dynamic nature. In most cases the link to the PHM aims is weakly established or indirect, as shown in Table 4.

Table 4: Summary of Impactibility Modelling examples

Authors	PHM approach / IM proposal	Outcome of interest / Link to PHM aims	Explanatory variables / Link to PHM aims	Criteria derivation	Location / Model type
Cohen et al. 2015 (73)	Approach A Proposal 1 & 2	Improve cost-effectiveness of case management <i>Implied PHM aims of reducing costs and improving health</i> <i>The link is indirect</i>	Patient characteristics and medical complexities such as active cancer, schizophrenia, resident in a nursing home, care arrangement or age. <i>Not explicit on implications to PHM aims</i>	Impactibility criteria are rules for exclusion based on clinical judgement	Israel IM is built as a refinement to RS model using routine health data
Buja et al. 2019 (56)	Approach A Proposal 1	Hospital admissions for heart failure patients <i>Implied PHM aims of reduce cost and improve health</i> <i>The link is indirect</i>	Algorithm based on clinical judgement for morbidity groupings for expected utilisation <i>Not explicit on implications to PHM aims</i>	Impactibility criteria are data-driven criteria from routine health data Using a variable defined by clinical judgement to form homogeneous sub-groups based on mortality	Italy IM built as a refinement to RS model using routine health data

Authors	PHM approach / IM proposal	Outcome of interest / Link to PHM aims	Explanatory variables / Link to PHM aims	Criteria derivation	Location / Model type
Stokes et al. 2017 (52)	Approach A Proposal 1	Effectiveness of intervention as measured by secondary care utilisation and cost measures <i>Implied PHM aims of reducing cost and improving health</i> <i>Direct link made to cost</i>	Disease measures including counts, clusters, complexity, mental and physical, and discordant co-morbidities <i>Not explicit on implications to PHM aims</i>	Impactibility criteria are data-driven based on routine health data	UK IM built using difference-in-difference analysis
Dubard and Jackson 2018 (72)	Approach B Proposal 5	Improving cost-effectiveness of case management defined as potential cost saving (expected vs actual cost) <i>Direct link to PHM aim of reducing cost.</i>	Demographic, clinical and utilisation characteristics <i>Not explicit on implications to PHM aims</i>	Impactibility criteria are data-driven based on routine health and claims data	USA IM built using linear regression model to predict potential cost savings.

4.6.2 Recommendations for development and application in practice

Common themes in the recommendations have been distilled into an ethos of IM including the need for: awareness, clarity, collaboration, preparedness and work across a wider health system. Where these recommendations are apparent from the literature these are summarised, in Table 5, without further elaboration.

The objective of PHM is to optimise health by working across the wider health system, inclusive but not restricted to the health and social care system. In the literature, there is potential for IM to develop with a restricted scope; proposal 4 limits the potential of population analysis to the health and social care system, as does a focus on tertiary prevention.

Structural changes, considered necessary for the sustainability of the UK health system, require action and collaboration across the wider health system (4, 5). Engaging wider health system stakeholders including local communities, authorities, and employers and adopting earlier prevention to tackle modifiable risk factors are key to the addressing sustainability pressures (4). In PHM, resources are allocated in the most effective to optimise health(10) and a better understanding of the drivers of risk and impactability, may more effectively direct resources to public health.

If the means of achieving cost savings is to be prevention of medical and social needs (and a resulting reduction of demand on services), then broader, population wide, approaches might prove better use of resources rather than the current focus on selecting specific patients for intensive health care services. (8)(p.249)

To achieve PHM aims, analysis and action should not be restricted in view (8, 13, 23, 55, 75). A specific recommendation is made here to ensure that work across the wider health system is paramount at this early stage of IM development.

Table 5: Impactability Modelling recommendations – An ethos of IM

A	Awareness
A1.	The role IM plays within a PHM system, depends on the approach adopted (A or B) which alters the design and objectives of IM. Those adopting IM should be cautiously aware of the ethical implications and the acceptability of IM under each approach.
A2.	Awareness of the timeliness, quality and adequacy of routine administrative health data for deriving impactability criteria is required. Further analysis may be required to understand the drivers of impactability.

A3.	Impactibility criteria can be based on clinical judgement, rules, and data-driven methods but developers should be aware that a combination of these criteria may be more effective. In addition, a model that includes common clinical judgement criteria and a model that interacts with clinical judgement may be more acceptable.
A4.	Developers should be cautiously aware of the implications of existing financial incentives and the role they play in the design of IM.
A5.	Those adopting and developing IM should be cautiously aware and actively consider the ethical implication of each element of the model design.
A6.	Awareness should be brought to the PHM aim of patient experience and how it will be represented and measured.
B	Clarity
B1	<p>Developers should be clear on the objectives of the PHM system.</p> <p>Clarity is required on why and how managing the outcome of interest is expected to achieve the PHM aims. In addition, clarity is required on how the choice of explanatory variables has implications on the achievement of each PHM aims.</p> <p>Best practice may be to create a direct link to the PHM aims where possible or to be explicit in the assumption of an indirect link to the PHM aims.</p>
B2	<p>Being clear on the relative importance of each PHM aim in the local context is a crucial stage in IM development.</p> <p>This is expected to improve inter-professional communications regarding the objectives of IM and provide clear evaluation terms.</p>
C	Collaboration
C1	The nature of the problem faced must be understood first when developing IM. This requires analysts and modellers to work in close collaboration with local practitioners, patients and the public representatives. This is also beneficial when defining evaluation terms in advance.
C2	Engagement with local healthcare teams and services users when deriving impactibility criteria is considered beneficial for successful implementation.
C3	Successfully embedding IM into an LHS requires training, support and proactive inter-professional communication. However, it also requires mutual-learning and establishing a common objective across stakeholders; to optimise health under constraints.
D	Preparedness
D1	The evaluation should be set out in advance. This will require a decision on: method, data, and terms of success including the relative weight of the PHM aims and short, medium and long-term KPIs.
D2	Intended and unintended consequences should be documented for regular evaluation. The risk of unintended consequences and mal-incentives should be explicitly considered during the design and objective setting of IM and PHM evaluation.

D3	IM developers will need to agree an ethical framework in advance for model design and implementation. Although models may be designed and implemented at a local level, it may be more suitable to agree an ethics framework at a more strategic level.
D4	IM should be tested for fit to the historic data and predictive accuracy. IM should be evaluated against its ability to contribute to each of the PHM aims. It could be used in comparative effective analysis of interventions.
E	Work across the wider health system
E1	When developing IM, it is important to consider its wider context in the PHM system and LHS. IM proposals should not limit the potential of PHM solutions to action within the health and social care system alone. Wider health system changes may be required to accommodate the dynamic problem of optimising health under constraints.
E2	Interventions from upstream to downstream prevention should be assessed for impactability. A lack of impactability is not a reason not to act. Impactability criteria can be leveraged to stratify and target intervention at earlier prevention stages. Alternatively, it should be used as a reason to improve interventions effectiveness.
E3	Designing IM in a PHM system for the better achievement of the PHM aims may not the same as designing IM to meet current financial incentives. PHM systems and IM models should be designed to meet the PHM aims (over current financial remuneration incentives).

4.6.3 Search strengths and limitations

Email correspondence with Lewis on 27 August 2019, gave confidence in the relevance and breadth of the literature captured. Seed authors are likely to cite their own or colleagues works which may have reduced the breadth of literature. However, the lack of new literature from the term search was reassuring.

This literature search is less reproducible¹⁶ and the varied nature of the literature did not lend itself toward meaningful meta- or quality analysis. However, this was not required to achieve the objective of this review.

The literature found is believed to be an adequate reflection of IM, but it is only a small proportion of PHM literature. The narrower search criteria may mean some areas relevant to the development of IM are not included.

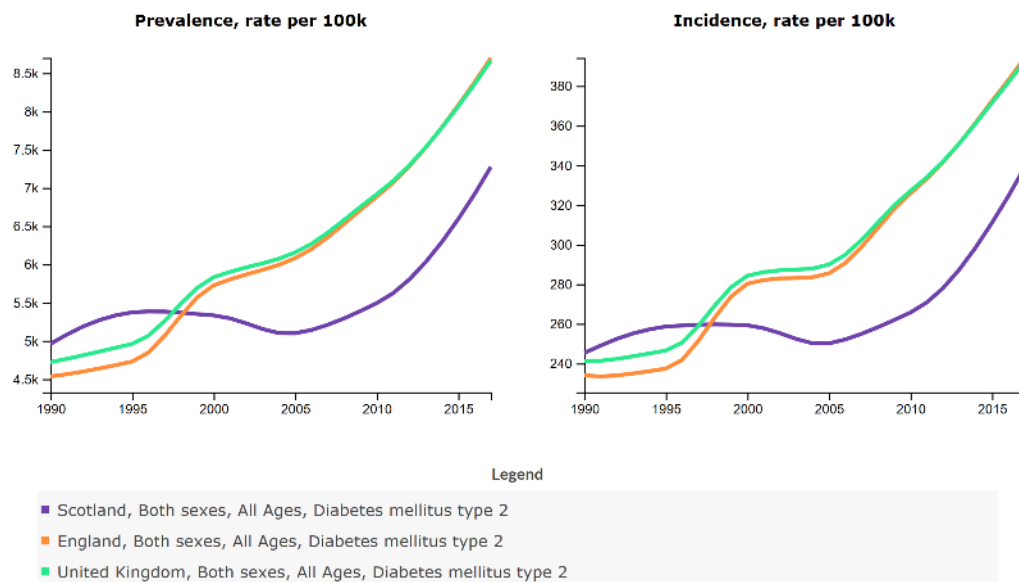
¹⁶ For transparency and completeness, Appendix 4 lists literature by relevance including those not considered relevant

Chapter 5 Proof of concept

5.1 Case study

Type 2 Diabetes Mellitus ('T2DM') is used as a case study for the proof of concept. Chronic diseases are long term conditions that cannot currently be cured but are controlled with a range of interventions and therefore contribute to demand-side pressures on a health system (26). T2DM "is a chronic metabolic condition characterised by insulin resistance ..and insufficient pancreatic insulin production, resulting in high blood glucose levels" (114) (p.6). The incidence and prevalence of the disease has been increasing in the UK (115), as shown in Figure 16, and the disease burden anticipated to increase in the future (116).

Figure 16: Prevalence and incidence of T2DM in England, Scotland and UK 1990-2017



Images sourced from IHME (115)

In the UK, the NHS Health Check provides secondary prevention screening for T2DM every 5 years from age 40 to 74 (117). At the same time, primary prevention is provided with advice on modifiable risk factor management to reduce the risk of T2DM (117).

5.2 Aims and objectives of proof of concept

To extend the development of IM, this proof of concept will expand on the clarity and awareness recommendations from Chapter 4 in the following ways:

- show how a model design can be directly associated with the PHM aims or explicit in the assumption of an indirect relationship;

- bring awareness to the implication for health inequalities of IM by testing socio-economic indicator as an impactibility criterion. At the same time, this shows how inequalities could be monitored on an ongoing basis; and
- show impactibility in terms of a modifiable risk factor thereby highlighting the importance of earlier stages of prevention to manage the outcome of interest.

The objective of this proof of concept is to explore the usefulness of MSM for the purpose of IM by:

- assessing if the model choice is suitable for routine health data;
- assessing if the model output can be used to interpret impactibility;
- showing how it could be used to derive impactibility criteria;
- providing output that can be used to evaluate IM accuracy; and
- providing output that can be used to evaluate intervention effectiveness.

To achieve these aims the following steps were undertaken:

1. Outline the theoretical suitability of MSM for application to routine health data, chronic disease analysis and various IM purposes;
2. Source routine health data which contains anonymised medical and demographic data including health outcomes;
3. Design and describe the cohort extracted suitable for a proof of concept analysis;
4. Consider potential sources of bias and confounders;
5. Define the IM outcome of interest and explanatory variables in direct relation to PHM aims and/or be explicit in the assumed indirect link to the PHM aims;
6. Describe the data used in the model including patient observations;
7. Describe the transition intensities, transition probability, mean sojourn times and total length of times in terms of impactibility;
8. Test if socio-economic indicator differentiates transition intensities; and
9. Test the model for fit to historic data and predictive accuracy.

Chapter 6 Methods

This chapter details the rationale for multi-state modelling ('MSM') as a method for IM and provides a description of the method as applied to T2DM.

6.1 Rationale for approach

MSM is suitable for PM as it “provides a natural and powerful framework” for describing and analysing life history processes and for that reason it is used in medicine, public health, economics and social sciences (118)(p.xiii). The outputs contain insights to “the probability of moving from one state to another, and the duration of spells spent in specific states”(118)(p.2) which are useful for interpreting impactibility when related to a cost or health state.

MSM “can be used to address a wide range of issues related to chronic diseases”(118)(p.6) so is applicable to the case study and a source of sustainability pressure. The model can be used for many objectives, as shown in Table 6, which not only align with the data-driven derivation of impactibility criteria but also with resource allocation and intervention evaluation.

Table 6: Multi-state modelling objectives

1	increasing the understanding of individuals' processes and of variation across individuals, groups or populations;
2	identifying and characterizing relationships between processes and covariates, or between two or more processes;
3	identifying risk factors associated with adverse outcomes;
4	assessing the effectiveness of individual or population level interventions; and
5	developing predictive models that can be used for activities such as resource allocation, policy formulation and patient management

Sourced from Cook & Lawless (118)(p.12)

MSM uses longitudinal data which covers an individual's life over a period of time including medical events and patient characteristics (118). It can accommodate routine health data of intermittent observation and uninformative truncation or censoring ¹⁷.

¹⁷ For background information on the method, a working description of MSM theory is provided in Appendix 8.

6.2 Description of the methods

An individual's life history is considered as "represented by time spent in states and movement between states" (119) (p.256). An individual can occupy one of the possible "states" at any given time and moves between states at random times governed by the probabilistic model" (119) (p.xv). To apply MSM, a state space and transition intensity matrix must be defined, and life history data sourced to populate the matrix. A description of how MSM is applied to T2DM for the objective of IM is provided here¹⁸.

6.2.1 State space

In this proof of concept, the management of the outcome of interest is related directly to the management of the disease and therefore the PHM aim of improving health status. Two models are defined based on measurements in the T2DM care guidelines (114, 120). Haemoglobin A1c ('HbA1C') is a clinical measure used for diagnosis and ongoing disease management; it is a measurement of blood glucose levels in the last 3 months (114, 121). Body Mass Index ('BMI') is a modifiable risk factor for T2DM before diagnosis and a target of lifestyle interventions after (114, 122). To overcome issues of short-term variation and measurement error when using raw biomarker values, states are defined in terms of ranges (118).

A deceased state is added to both models, as an absorbing state, to account for mortality risk during the period.

6.2.1.1 BMI model

For BMI, the well-established ranges shown in Table 7, are adopted for the model states (122).

Table 7: BMI ranges by nutritional status

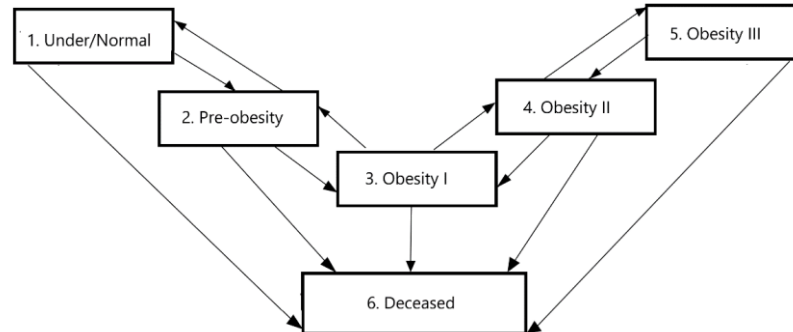
BMI	Nutritional Status
Below 18.5	Underweight
18.5 – 24.9	Normal weight
25.0 – 29.9	Pre-obesity
30.0 – 34.9	Obesity Class I
35.0 – 39.9	Obesity Class II
40 and above	Obesity Class III

Categorisation as provided by World Health Organisation(122)

¹⁸ For background information on the method, a working description of MSM theory is provided in Appendix 8.

The underweight category is grouped with normal weight due to a lack of data which creates the state space represented in Figure 17.

Figure 17: BMI model state space



6.2.1.2 HbA1c model

Once diagnosed, ranges of HbA1c are used to categorise the management of the chronic condition, as shown in Table 8.

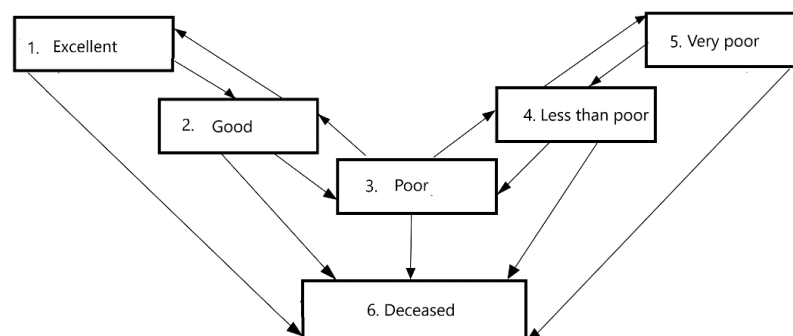
Table 8: HbA1c ranges by diabetes control

HbA1c %	mmol/mol	Diabetes control
Below 5.9	31 - 49	Excellent
5.9 – 6.6	50 - 55	Good
6.7 – 7.2	56 – 60	Poor
7.3 – 8.6	61 – 70	Less than poor
8.7 and above	71 +	Very poor

Categorisation from Southend NHS (123)

These ranges have been adopted as states for the model, as represented in Figure 18.

Figure 18: HbA1c model state space



6.2.2 Transition intensity matrix

Transition intensities are the forces to which an individual is subject; keeping the individual in the current state or transitioning to another state. Data is analysed to populate the transition intensity matrix, Q , as shown in Equation 1. Transitions that are not possible in the process are set to zero. The instantaneous transition rate to remain in the same state is the negative of the sum of transition rates to leave the state i.e. $\mu_x^{11} = -(\mu_x^{12} + \mu_x^{16})$. The structure of the matrices is the same for both models as there is the same number of states and allowable movements between states.

Equation 1: Transition intensity matrix

$$Q(t) = \begin{bmatrix} \mu_x^{11} & \mu_x^{12} & 0 & 0 & 0 & \mu_x^{16} \\ \mu_x^{21} & \mu_x^{22} & \mu_x^{23} & 0 & 0 & \mu_x^{26} \\ 0 & \mu_x^{32} & \mu_x^{33} & \mu_x^{34} & 0 & \mu_x^{36} \\ 0 & 0 & \mu_x^{43} & \mu_x^{44} & \mu_x^{45} & \mu_x^{46} \\ 0 & 0 & 0 & \mu_x^{54} & \mu_x^{55} & \mu_x^{56} \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

6.2.2.1 Explanatory Variable

Testing for an explanatory variable is the first step in deriving impactibility criteria. In a MSM, an explanatory variable can be added to the model to test if transition rates vary significantly by that factor.

The PHM aim of reducing health inequalities is built directly into this proof of concept by testing the socio-economic indicator, Scottish IMD¹⁹, as an explanatory variable for impactibility. IMD is known to be correlated with health inequalities (124, 125). Two IMD groups are created; most deprived including IMD deciles 1 to 5 and least deprived including deciles 6 to 10.

If transition rates toward unhealthier ranges of BMI and HbA1c (progression through states) are higher or if transition rates toward healthier ranges of BMI and HbA1c (regression through states) are lower – then a patient would have lower impactibility. By testing if transition rates vary by IMD, an awareness is brought to the implications of IM for health inequalities under approach A or B.

¹⁹ The Scottish Index of Multiple Deprivation ('SIMD') is used in this dataset and is referred to hereafter as IMD.

6.2.3 Data

Individual life history data is required to populate the transition intensity matrix. There are a number of BMI or HbA1c observations recorded in a patients' data and these are considered as events in MSM.

6.2.3.1 Source

Retrospective cohort data access was agreed for research purposes with the University of Edinburgh²⁰. The Scottish Care Information ('SCI') diabetes epidemiology database²¹ is a population disease register for diabetes in Scotland sourced from linked routine primary and secondary care health data with good coverage (126). The 2016 dataset is the most recent available which contains anonymised and cleaned medical event and demographic data for patients with T2DM.

6.2.3.2 Cohort

To account for confounders a fully comprehensive model would need to be more complex than is within the project scope. In the spirit of a proof of concept and for model parsimony, simplifying criteria are applied to create a more homogeneous test cohort. A summary of these criteria provided in Table 9.

Table 9: Defining cohort criteria

Criteria	Restriction
Time period	Events occurring between 01/01/2011 and 15/07/2016
Diabetes type	T2DM excluding gestational and secondary diabetes
Gender	Both men and women
Age	Aged [40, 49] at diagnosis
Durations	First 5 years following diagnosis
Intervention	All under 'current practice'

The time period is defined to ensure the cohort represents the most recent period in the dataset for which there are no material changes to guideline interventions (114, 120). Analysis is restricted to T2DM in adults excluding secondary and gestational diabetes to mirror care guideline (114). Ages 40 to 49 at diagnosis, inclusive, represent the youngest range of the target T2DM primary and secondary prevention ages (117) where the prevalence of multi-morbidities is anticipated to be lower than older target ages. Age is likely to be an explanatory variable (127-129) but the transition rates are assumed not to vary materially in the 10-year range for the proof of concept. Duration since diagnosis may be an

²⁰ A Level 1 Ethics form is provided in Appendix 1, no further review was required.

²¹ Referred to hereafter as the SCI database

explanatory variable in the control of HbA1c (130) or BMI. For simplicity, the first 5-years after diagnosis are chosen for the cohort and it is assumed there is not a material change in transition rates over this period.

Population level data may indicate impactibility for a given intervention however, to allow for a simplified analysis, this proof of concept assesses the range of guideline interventions used in the first 5-years of diagnosis under 'current practice'. Guidelines include lifestyle changes, patient education and self-management alongside medicinal therapy (114, 120). There will be variation to suit the individual (114, 120) but it is assumed that care is adequately and appropriately provided as T2DM is an ACSC with an established Audit and Feedback practice, linked to Quality and Outcome Framework ('QOF') for practitioner remuneration (131).

6.2.3.3 Potential sources of bias

The data is assumed to be representative of the Scottish T2DM population with limited scope for selection bias (126). The retrospective data is based on routine health data; patients are not self-selected for research.

The cohort includes patients in allowable states between the study start and end dates. HbA1c is recorded for over 90% of the population and BMI for over 80% (132). There is considered to be no bias in the patients missing HbA1c or BMI, as these are measures for disease management (132, 133). In addition, only patients with more than one observation are included to allow for time between events to be analysed. Patients with only one event in a 5-year period are not assumed to be inherently different.

The data covers all of Scotland so 'loss to follow up' bias is limited to emigration out of Scotland in a 5-year period. Right censoring where patients leave before an event occurs is allowed for in the state space by ensuring all modes of exit are accounted for. It is assumed there are no other material forms of exit than death.

Only patients diagnosed after the study start date are included which removes left censoring and truncation issues where people are at-risk, or the event occurred, before the study start date, respectively.

MSM can cope with non-informative left-truncation and right-censoring as the indicator function considers time under observation only. Based on the above, it is assumed both are non-informative within the dataset.

In observational data "the collection of data can occur sporadically at times that vary from individual to individual" (118)(p.3). This is common to routine health administration data

where an observation is made if the individual presents to the medical system. MSM is suitable for analysis of this 'panel data' with intermittent observation (118).

The provision of private health care for chronic disease is considered not to be material. Therefore, the risk of event data being recorded outside of the database is considered minimal as the SCI database links public primary and secondary care. Patients missing postcode removed only 0.2% of the cohort and is not considered to introduce bias.

Some data may be recorded with greater accuracy in observation data than others. For states other than deceased, the dates are assumed to be non-exact (observational), but date of death is assumed to be exact in the model design.

6.2.4 Computation, data manipulation and model testing

The *msm* package in R is used for computation (134). This off-the-shelf model has a useful guide (134) and based in a free access programme making it appropriate for work in multi-disciplinary teams and across institutions. A data frame of a counting process format is prepared with the variables: unique ID, state, time, IMD group²².

The model should be capable of generating the observed data (119)(p.258) when well fitted therefore it is important to create two datasets to prevent overfitting; one to train the model and another to validate predictive accuracy (25). The full dataset is split into a training (75%) and validation (25%) dataset using uniform distribution random numbers. As the model was not fit on the validation data, it provides an indication of the predictive accuracy.

The model build is specified by the state space and the transition matrix. Under each model transition rates were solved for and then IMD group tested as an explanatory variable. No model selection was required as this proof of concept only tests if the covariate provided explanatory power. Suitable MSM diagnostic checks of Observed vs Expected analysis are performed.

6.2.5 Potential confounders

Variation in the ability to control HbA1c or keep a healthy BMI following diagnosis may vary by gender, age, duration, and morbidity (135, 136). The affect by IMD may be confounded by the variation of these factors by IMD group in the data. Evidence of possible confounding was analysed for these four factors using visual graph comparison.

²² An example data frame is provided in Appendix 9

It is not possible to check due to poor data coverage but there may be a bias in the distribution of ethnicity by IMD. It is assumed that there is no bias in medical adherence by IMD group under free healthcare and affordable prescriptions. There is likely to be smoking prevalence bias by IMD group however, smoking is not considered to impact BMI or Hba1C (137).

Chapter 7 Results

This chapter provides a data summary and results for each model.

7.1 Data summary

7.1.1 Count of patients

A total of 11,240 patients were included in the BMI model and 13,364 in the HbA1c model, as shown in Table 10 and Table 11. Approximately 60% of T2DM patients are in the most deprived IMD group.

Table 10: BMI data summary - count of patients

Dataset	Full	Training	Validation
Total patients	11,240	8,485	2,755
Most deprived IMD[1,5]	7,118	5,384	1,734
Least deprived IMD [6,10]	4,122	3,101	1,021

Table 11: HbA1c data summary - count of patients

Dataset	Full	Training	Validation
Total patients	13,364	9,902	3,444
Most deprived IMD[1,5]	8,485	6,310	2,175
Least deprived IMD [6,10]	4,879	3,610	1,269

7.1.2 Count of observations

The median number of observations per patient in the data is 4 for BMI and 6 for HbA1c in a 5-year period. The number of observations is similarly distributed by IMD group, as shown in Table 12 and Table 13²³. This implies that one group is not contributing more information to a model than the other.

Table 12: BMI data summary - count of observations

Dataset	Full		Training	Validation
	Most deprived	Least deprived	All IMD	All IMD
Min	2	2	2	2
Q1	3	3	3	3
Median	4	4	4	4
Q3	6	6	6	6
Max	74	54	74	31
Mean	4.86	4.77	4.81	4.77

²³ A graph of the distribution of observation is provided in Appendix 11.

Table 13: HbA1c data summary - count of observations

Dataset	Full		Training	Validation
	Most deprived	Least deprived	All IMD	All IMD
Min	2	2	2	2
Q1	4	4	4	4
Median	6	6	6	6
Q3	8	9	8	8
Max	33	40	40	33
Mean	6.37	6.45	6.42	6.36

7.1.3 Observed transitions

The transitions between states observed in the training datasets, shown in Table 14 and Table 15, are used to populate the model²⁴.

This can be read as there were 35 transitioned *from* a state of Pre-obesity *to* Deceased. There were 7,996 observation of Obesity 1 followed next by an observation of Obesity 1.

Table 14: BMI observed transitions

State	To					
From	Under/Normal	Pre-obesity	Obesity 1	Obesity 2	Obesity 3	Deceased
Under/Normal	2,000	187	2	0	0	25
Pre-obesity	225	4,931	510	1	0	35
Obesity 1	2	614	7,996	517	1	31
Obesity 2	1	2	700	6,314	403	23
Obesity 3	0	0	8	560	7,259	29
Deceased	0	0	0	0	0	0

When most of the observations lie on the diagonal of the matrix, i.e. not changing state, the process is said to be more stationary. The BMI process is more stationary than HbA1c, as seen in Table 15.

Table 15: HbA1c observed transitions

State	To					
From	Excellent	Good	Poor	Less than poor	Very poor	Deceased
Excellent	10,580	2,232	653	493	374	57
Good	2,233	3,261	1,456	1,217	762	20
Poor	715	1,308	1,433	1,389	831	12
Less than poor	761	1,308	1,471	3,166	2,191	19
Very poor	794	935	969	2,905	10,123	50
Deceased	-	-	-	-	-	-

²⁴ Observed transitions by IMD group are shown in Appendix 11.

7.2 Potential confounder analysis

There is no visible bias in the distribution of data by IMD group by gender (Figure 19), age at diagnosis (Figure 20) or duration since diagnosis (Figure 21).

Figure 19: Gender distribution of patients by IMD

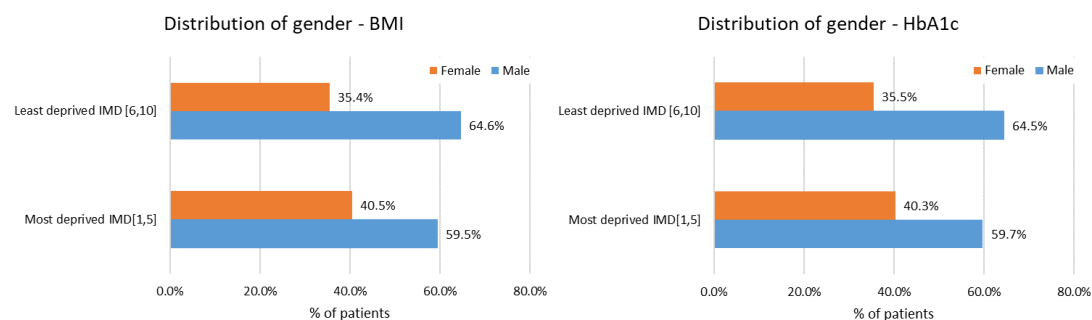


Figure 20: Age at diagnosis distribution of patients by IMD

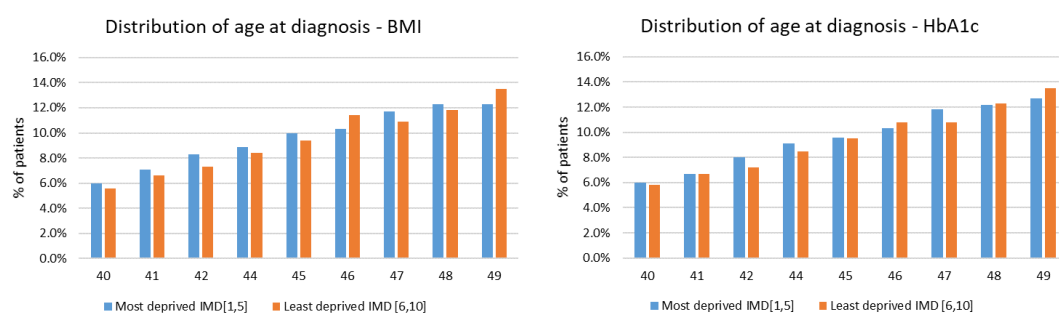
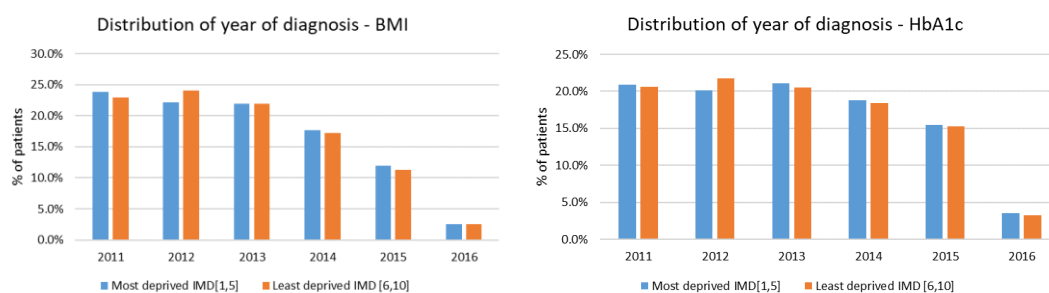


Figure 21: Year of diagnosis distribution of patients by IMD



There is no visible bias in the prevalence of morbidities by IMD in Figure 22 and Figure 23. A modified Charlson Index (138, 139) shows the severity of existing morbidities in the 10-years

prior to diagnosis²⁵. There is a bias toward morbidities especially at higher severities in the most deprived group however, this is limited for more sever morbidities to around 1%.

Figure 22: Morbidity distribution of patients by IMD – BMI dataset

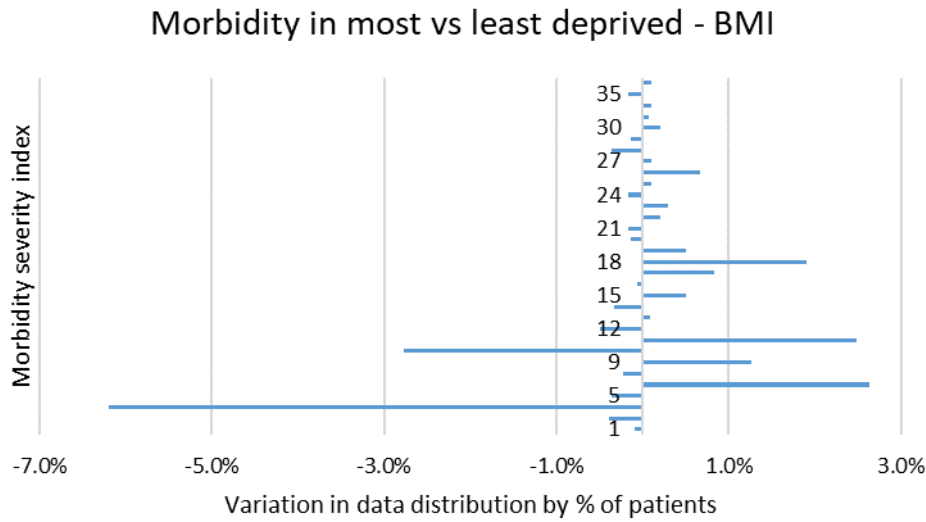
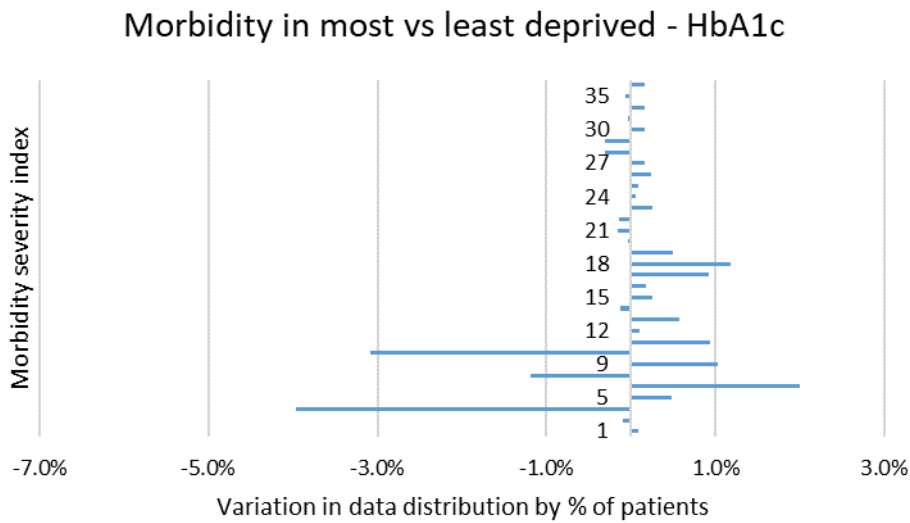


Figure 23: Morbidity distribution of patients by IMD – HbA1c dataset



²⁵ Code was kindly sourced from Kelly Fleetwood at the University of Edinburgh.

7.3 Rates

From the defined state space, transition intensities, μ_{x+t}^{jk} , are inferred from the observed data and are the basis for all other output rates. These can be translated into transition probabilities, ${}_t p_x^{ij}$, that show, over longer time periods, how likely a patient is to transition from one state to another. The average length of time in a certain state before moving to another, the sojourn time, can also be calculated along with the total time spent in a state over a period.

7.3.1 Transition intensities

Without consideration for covariates, the estimates of transition intensities, μ_x^{ij} , are shown in Table 16 and Table 17, along with a 95% confidence interval. The final column is the force of mortality from each state. An interpretation of the rates is provided for each model.

7.3.1.1 BMI model

An individual who is Pre-obesity is 2.5 (0.015/0.06) times more likely to move to Obesity 1 than Under/Normal BMI. Those in Obesity 1 and 2 are only a little more likely to lose weight than gain weight.

7.3.1.2 HbA1c model

An individual who has Good HbA1c is 2.5 (0.409/0.165) times more likely to move to Poor than Excellent HbA1c. Those with Poor control are almost equally likely to progress or regress. Those with Less than poor HbA1c are twice as likely to improve HbA1c control to Poor than progress to Very Poor.

Table 16: BMI model transition intensities

State	To					
From	Under/Normal	Pre-obesity	Obesity 1	Obesity 2	Obesity 3	Deceased
Under/Normal	-0.018 (-0.021, -0.016)	0.016 (0.014, 0.019)	-	-	-	0.002 (0.001, 0.003)
Pre-obesity	0.006 (0.006, 0.007)	-0.022 (-0.024, -0.021)	0.015 (0.014, 0.016)	-	-	0.001 (0.001, 0.001)
Obesity 1	-	0.012 (0.011, 0.012)	-0.022 (-0.023, -0.021)	0.010 (0.009, 0.011)	-	0.000 (0.000, 0.001)
Obesity 2	-	-	0.018 (0.017, 0.020)	-0.030 (-0.031, -0.028)	0.011 (0.010, 0.012)	0.000 (0.000, 0.001)
Obesity 3	-	-	-	0.015 (0.014, 0.016)	-0.016 (-0.017, -0.015)	0.001 (0.000, 0.001)

Table 17: HbA1c model transition intensities

State	To					
From	Excellent	Good	Poor	Less than poor	Very poor	Deceased
Excellent	-0.080 (-0.083, -0.076)	0.079 (0.076, 0.082)	-	-	-	0.001 (0.000, 0.001)
Good	0.165 (0.158, 0.171)	-0.574 (-0.605, -0.545)	0.409 (0.381, 0.440)	-	-	0.000 (0.000, 0.002)
Poor	-	0.672 (0.627, 0.720)	-1.402 (-1.463, -1.343)	0.729 (0.675, 0.788)	-	0.000 (0.000, 0.003)
Less than poor	-	-	0.521 (0.486, 0.559)	-0.755 (-0.793, -0.719)	0.233 (0.223, 0.244)	0.000 (0.000, 0.001)
Very poor	-	-	-	0.180 (0.173, 0.187)	-0.181 (-0.188, -0.174)	0.001 (0.000, 0.001)

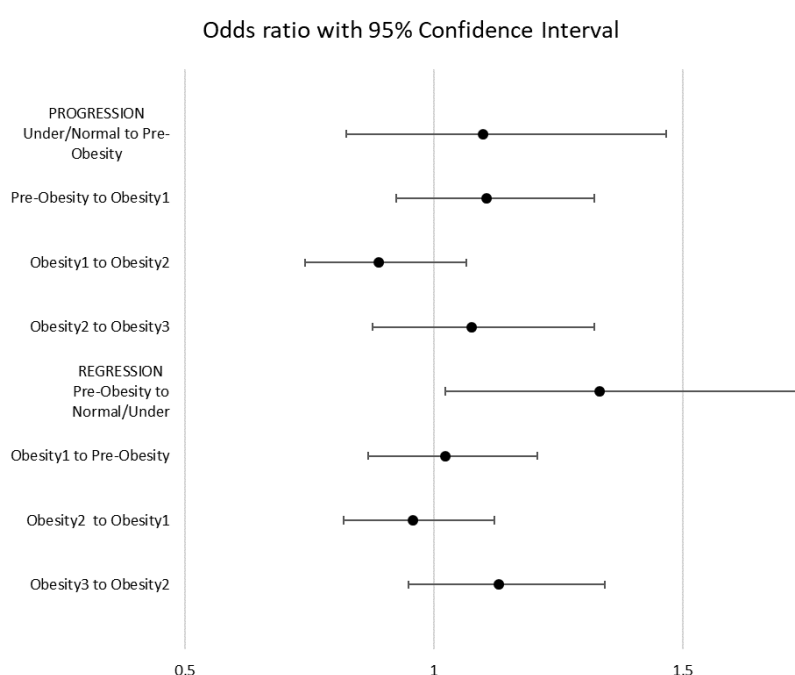
7.3.2 Explanatory variable

Neither model resulted in statistically significant difference in transition rates by IMD. The odds ratio, with 95% confidence interval, represents a comparison of the transition rates of the least deprived group to the baseline most deprived group. These are grouped into progression (worsening) or regression (improving) BMI and HbA1c states for interpretation for impactibility.

7.3.2.1 BMI model

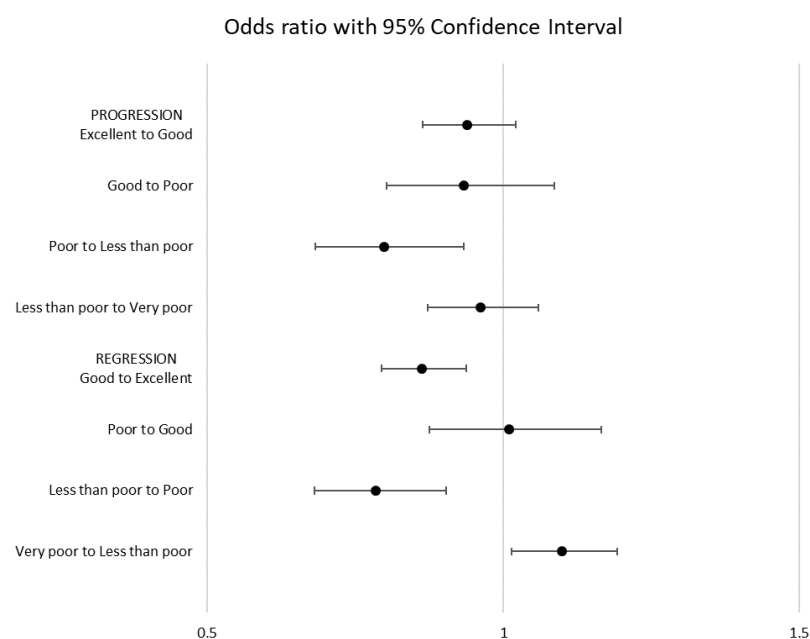
The confidence interval for the odds ratio generally cross 1 as shown in Figure 24.

Figure 24: BMI model - odds ratio of transition rates by IMD group



7.3.2.2 HbA1c model

The odds ratios significantly different to 1 in Figure 25 provide a mixed message; the least deprived group has lower transition intensities from Poor to Less than poor (higher impactibility), and lower transitions from Good to Excellent and Less than poor to Poor (lower impactibility) but higher transition from Very poor to Less than poor (high impactibility).

Figure 25: HbA1c model - odds ratio of transition rates by IMD group

7.3.3 Transition probabilities

Transition probability for 12- and 60-months periods are estimated.

7.3.3.1 BMI model

Table 18 shows that an individual with a BMI of Obesity 2 has a 72% chance of remaining in the same state in a 1-year period, compared to 10% of progressing to Obesity 3 and 16% chance of regressing to Obesity 1.

Over a 5-year period the probabilities of BMI changing states are higher, as shown in Table 19. For example, an individual with a BMI of Obesity 2 has a 32% chance of remaining in the same state over a 5-year period, compared to 20% of progressing to Obesity 3 and 44% chance of regressing to a lower BMI.

Table 18: BMI model transition probabilities (expressed as %) - 12 months

State From	To					
	Under/ Normal	Pre- obesity	Obesity 1	Obesity 2	Obesity 3	Deceased
Under/Normal	80.8	15.5	1.4	0.1	0.0	2.3
Pre-obesity	6.1	78.1	13.9	0.8	0.0	1.0
Obesity 1	0.4	10.7	78.8	8.9	0.6	0.6
Obesity 2	0.0	1.1	16.3	72.0	9.9	0.6
Obesity 3	0.0	0.1	1.5	13.9	83.7	0.8
Deceased	-	-	-	-	-	100.0

Table 19: BMI model transition probabilities (expressed as %) - 60 months

State	To					
From	Under/ Normal	Pre- obesity	Obesity 1	Obesity 2	Obesity 3	Deceased
Under/Normal	39.5	34.0	14.3	2.5	0.4	9.3
Pre-obesity	13.5	41.6	30.8	7.4	1.7	5.0
Obesity 1	4.4	23.7	45.2	17.5	5.9	3.3
Obesity 2	1.4	10.5	32.2	32.1	20.6	3.2
Obesity 3	0.3	3.4	15.2	28.9	48.5	3.7
Deceased	-	-	-	-	-	100.0

7.3.3.2 HbA1c model

Table 20 shows that an individual having a HbA1c of Less than poor has a 19% chance of remaining in the same state in a 1-year period, compared to 27% of progressing to a worse HbA1c and 52% chance of regressing to better HbA1c.

Table 20: HbA1c model transition probabilities (expressed as %) - 12 months

State	To					
From	Excellent	Good	Poor	Less than poor	Very poor	Deceased
Excellent	57.2	17.4	8.3	9.1	7.3	0.7
Good	36.3	18.9	11.3	15.3	17.6	0.6
Poor	28.5	18.6	12.1	17.5	22.7	0.6
Less than poor	22.4	18.0	12.5	19.1	27.4	0.6
Very poor	13.8	16.0	12.5	21.2	35.8	0.7
Deceased	-	-	-	-	-	100.0

Over a 5-year period the probabilities of HbA1c improving are higher, as shown in Table 21.

Table 21: HbA1c model transition probabilities (expressed %) - 60 months

State	To					
From	Excellent	Good	Poor	Less than poor	Very poor	Deceased
Excellent	36.2	17.2	10.4	14.5	18.6	3.2
Good	35.8	17.2	10.4	14.6	18.9	3.1
Poor	35.6	17.2	10.5	14.7	19.0	3.1
Less than poor	35.4	17.2	10.5	14.7	19.1	3.1
Very poor	35.1	17.1	10.5	14.8	19.3	3.2
Deceased	-	-	-	-	-	100.0

7.3.4 Mean sojourn time

Mean sojourn times show the average stay in a single state before transitioning to another and are provided with 95% confidence intervals.

7.3.4.1 BMI model

Table 22 shows that an individual diagnosed with T2DM with an Obesity 2 BMI is likely to remain in that state 2.8 years before transitioning.

Table 22: BMI model - mean sojourn times in months with 95% confidence interval

State	95% CI			
	Estimate	SE	Lower	Upper
Under/Normal	54.3	3.7	47.5	62.1
Pre-obesity	44.9	1.6	41.8	48.2
Obesity 1	45.6	1.4	43.0	48.4
Obesity 2	33.9	1	31.9	35.9
Obesity 3	63.5	2.6	58.6	68.9
Deceased	-	-	-	-

7.3.4.2 HbA1c model

Table 23 shows that an individual who has a Very poor HbA1c is likely to remain in that state almost half a year before transitioning.

Table 23: HbA1c model - mean sojourn times in months with 95% confidence interval

State	95% CI			
	Estimate	SE	Lower	Upper
Excellent	12.6	0.3	12.1	13.1
Good	1.7	0	1.7	1.8
Poor	0.7	0	0.7	0.7
Less than poor	1.3	0	1.3	1.4
Very poor	5.5	0.1	5.3	5.8

7.3.5 Total length of time

The estimated total length of time spent in each state is forecasted for an individual over a 60-month period.

7.3.5.1 BMI model

Table 24 shows that a Pre-obese individual is expected to have roughly half a year in Under/normal weight, 3 years in Pre-obesity and 1 year with Obesity 1 BMI in a 5-year period.

Table 24: BMI model - total length of time in months in a state - 60-months

State	To					
From	Under/ Normal	Pre- obesity	Obesity 1	Obesity 2	Obesity 3	Deceased
Under/Normal	38.0	14.6	3.8	0.5	0.1	3.1
Pre-obesity	5.8	37.3	13.1	2.1	0.3	1.5
Obesity 1	1.2	10.1	38.4	7.8	1.6	1.0
Obesity 2	0.3	2.9	14.4	32.5	9.1	0.9
Obesity 3	0.0	0.6	4.1	12.7	41.4	1.1
Deceased	-	-	-	-	-	60.0

7.3.5.2 HbA1c model

In Table 25, an individual with Poor HbA1c is expected to have roughly 1.5 years in Excellent, under 1 year in Good, just over half a year in Poor, under 1 year in Less than poor, and Very poor in a 5-year period.

Table 25: HbA1c model - total length of time in months in a state - 60-months

State	To					
From	Excellent	Good	Poor	Less than poor	Very poor	Deceased
Excellent	28.7	10.0	5.4	6.9	7.9	1.0
Good	20.9	12.3	6.8	8.8	10.4	0.9
Poor	18.6	11.1	7.6	10.0	11.8	0.9
Less than poor	17.0	10.4	7.1	11.2	13.4	0.9
Very poor	15.0	9.4	6.5	10.3	17.8	1.0
Deceased	-	-	-	-	-	60.0

7.4 Accuracy

The model is tested for its fit to the historic data using the training dataset and predictive accuracy using the validation dataset in an Expected vs Observed analysis.

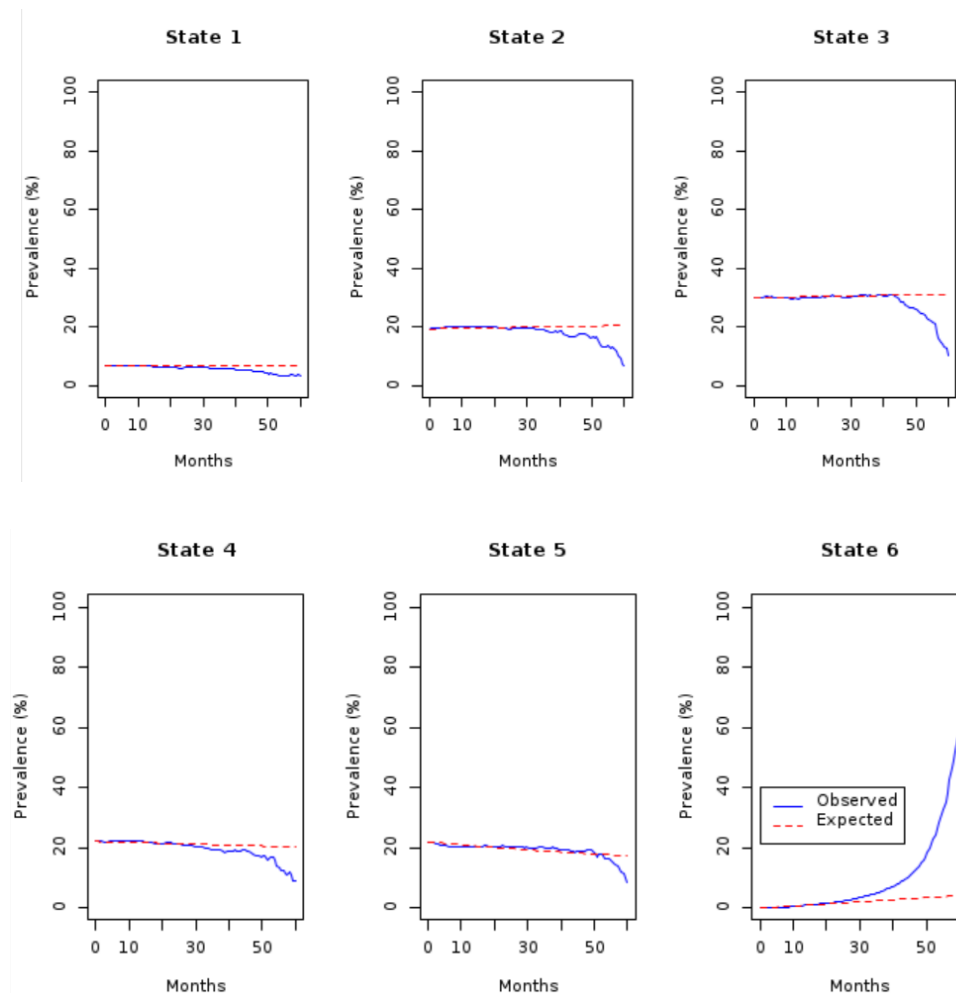
7.4.1 Fit to historic data

The transition rates are used to generate expected transitions which are compared to the observed transitions in the training dataset.

7.4.1.1 BMI model

The BMI model fit to the historic data is fair until 50-months, as shown in Figure 26. The model is greatly underestimating the number of deaths (State 6) which is causing an overestimation in other states.

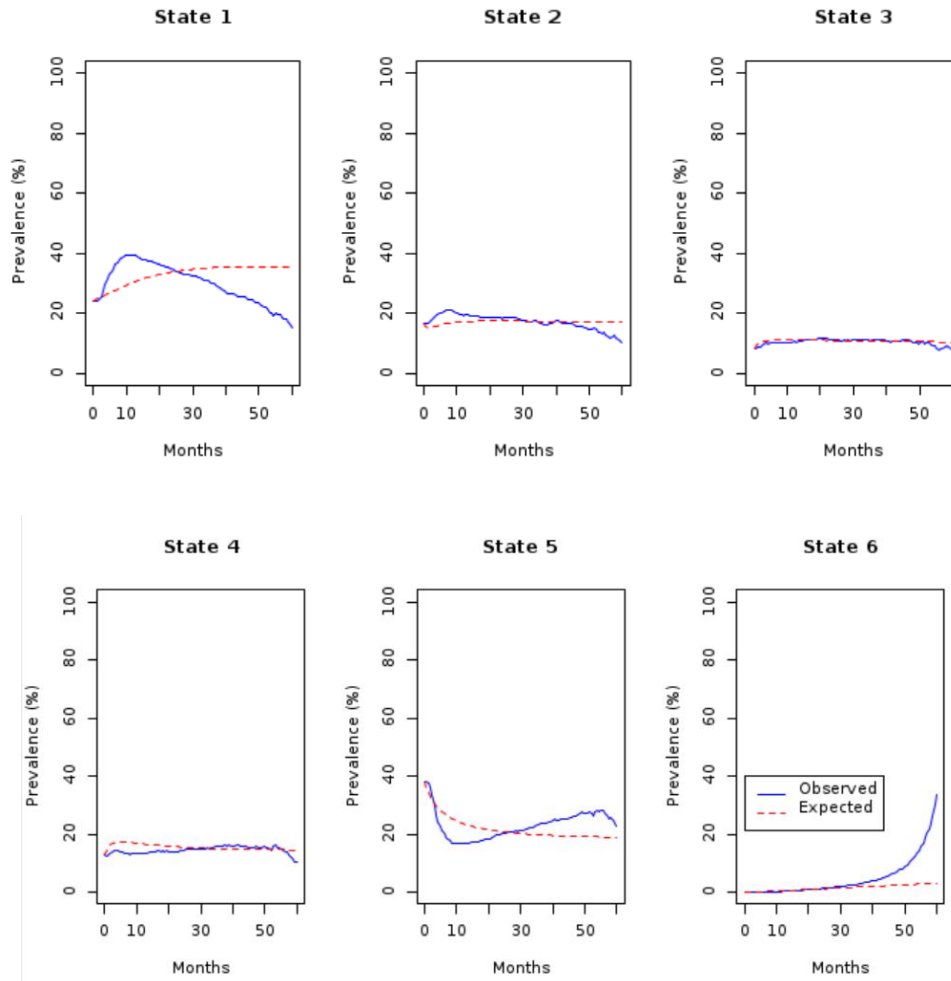
Figure 26: BMI model Observed vs Expected - historic data



7.4.1.2 HbA1C model

Similarly, the model is greatly underestimating the number of deaths (State 6), as shown in Figure 27. However, the model is also overestimating Excellent (State 1) and Very poor (State 5). A short-lived effect, i.e. durational, seen in Excellent and Very poor states is not being captured by the model²⁶.

Figure 27: HbA1c model Observed vs Expected - historic data



7.4.2 Predictive accuracy

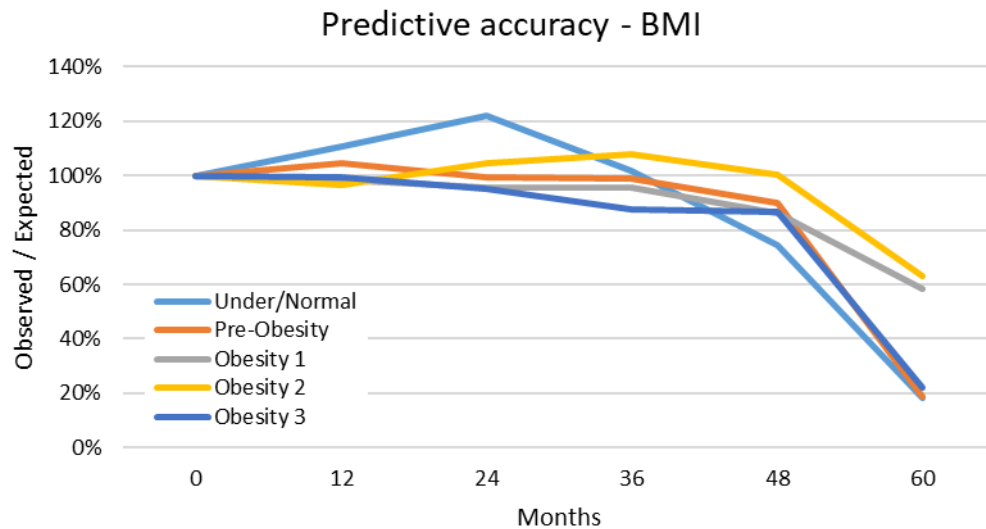
The transition rates are used to generate expected transition based on the validation dataset and compared to the observed transitions. The impact of transition intensity inaccuracies accumulates over time causing the fit to deteriorate.

²⁶ Further interpretation is provided in the discussion in Section 8.2.

7.4.2.1 BMI model

The predictive accuracy of the BMI model is fair at shorter time periods but is not useable after 4-years, as shown in Figure 28. The predictive accuracy for Under/Normal is poor due to lower data volumes.

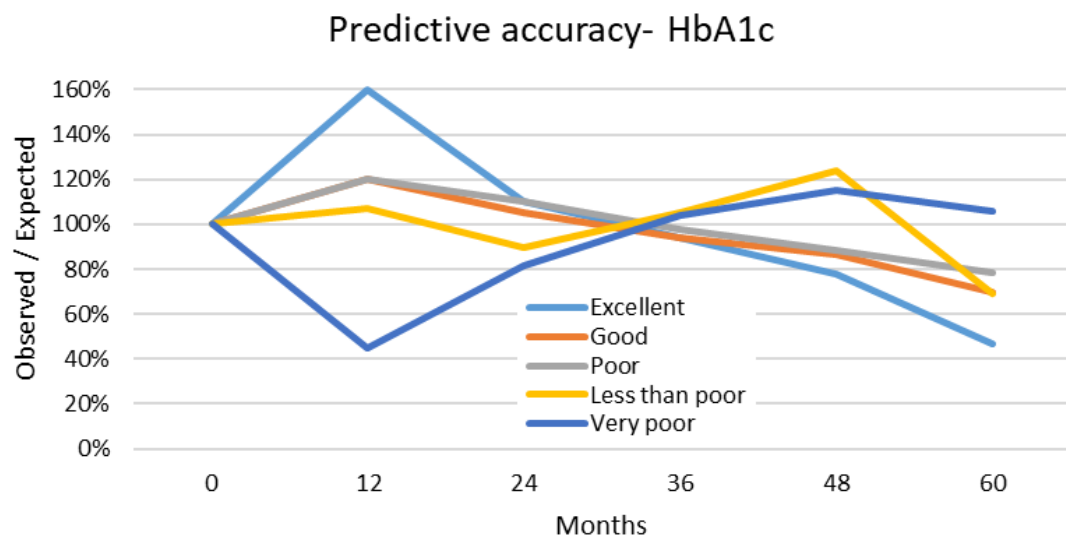
Figure 28: BMI model O/E ratio - predicted accuracy



7.4.2.2 HbA1C model

The predictive accuracy of the HbA1c model is poor at shorter time periods especially for the extreme ranges of HbA1c, as shown in Figure 29.

Figure 29: HbA1c model O/E ratio - predictive accuracy



Chapter 8 Discussion

8.1 Summary of findings

Transition rates for BMI and HbA1c in the first 5-years of diagnosis for ages 40 to 49 inclusive, under 'current practice' interventions, were modelled to assess impactibility using MSM. The model design has weaknesses impacting its accuracy but as a proof of concept for IM the choice of MSM is positive.

MSM may be a useful tool for the purpose of IM for several reasons: it is suitable for the analysis routine health data; it can be used for multiple objectives which align to IM use, and; it provides insight into the time spent in different states from which impactibility can be inferred when related to cost or health status.

This proof of concept model illustrates how some recommendations made in Chapter 4 could be applied in practice, namely clarity and awareness.

The model design has been related to the PHM aims by linking the outcome of interest to BMI and HbA1c. Control of HbA1c is considered to reduce the impact of diabetes and risk of sequelae (71, 114) and BMI is a target of lifestyle interventions (114). Therefore, impactable people could be considered as those who: regress through states by decreasing BMI or HbA1c; or people who spend longer in healthier states such as lower BMI or controlled HbA1c states.

Creating an impact on these measures would directly improve health status and, is indirectly assumed to reduce costs. The many sequelae of T2DM require high health service utilisation (4, 71, 114). The risk of sequelae are assumed to decrease with improved HbA1c and BMI (114, 140, 141) and therefore the utilisation and costs should reduce in proportion. This assumption is made explicitly and would need to be evaluated.

Patient experience would require separate evaluation.

A barrier to successful IM implementation is the concern regarding inequalities (27). This simplified model was not able to show that transition rates vary by IMD. However, it is not proposed that this is taken in evidence against these concerns but shows how a model can be created to assess if impactibility varies by variables associated with health inequalities during design and ongoing evaluation.

Testing an explanatory variable is a step in deriving impactibility criteria. In this proof of concept, impactibility criteria were not derived however odd ratios produced by MSM can test

the significance of explanatory variables for that purpose. The same process could be used to monitor the consequences of chosen impactability criteria on health inequalities. MSM can produce survival duration; a common clinical judgement impactability criterion.

The accuracy of IM using MSM can be evaluated using fit to historic data and predictive accuracy with observed vs expected analysis. The funnel of doubt in making predictions widens with time and therefore rates that more accurately account for the underlying process are preferred for long-term forecasts.

It is important to establish that a model in its own right is neither ethical nor unethical, only the use of the outputs can be judged as such. A model may lend itself to highlight impactability by variables that correlate to health inequalities, but it is the model user who decides how to implement the results.

Impactability assessed in terms of BMI, a modifiable risk factor, highlights the importance of earlier stages of prevention; as at an individual level the drivers of impactability may be “highly resistant to change”(8)(p.249) as evidenced by the relative stationarity in the BMI process. For chronic diseases like T2DM there is a “need to look beyond simply providing medical care, toward services which address patients’ broader social and behavioural health needs” (79)(p.2018). The results of IM analysis could be used to promote and target earlier stages of prevention and work across the wider health system. For example, the age of NHS Health Check could be brought forward where there is a lack of impactability.

8.2 Strengths and limitations

More complex modelling techniques have been suggest (142) but there is a place for MSM when producing insights to work across the wider health system. The strengths and limitations of this proof of concept are considered in terms of the data and study design.

8.2.1 Data

The SCI database is of good quality but is not timely with insights 3-years lagged. IM must overcome data time lags to produce actionable predictions.

For this case study, the outcome of interest was available in the data with good coverage and quality. However, the scope of IM may be limited to use cases where health outcome data pre-exists.

The dataset created for this proof of concept was minimally defined however increased linkage and additional variables could increase the actionable impactability insights. The data will only ever represent an impression of a person and will be missing many important

variables (80). For example, ethnicity was not well populated in the dataset and work was not undertaken to link social factors.

8.2.2 Study design

The study design can be assessed by the state space, transition intensity matrix, cohort and explanatory variable test.

8.2.2.1 State space and transition intensity matrix

A balance between the number of states and credibility of results is an important model choice (143). Defining a 6-state space for HbA1c and BMI provides increased granularity to assess impactibility.

However, for lower data volumes in the Under/Normal category influenced the accuracy of the BMI model estimates. To improve accuracy in the future, Under/Normal could be grouped with Pre-obesity.

Goel et al. recently published a MSM for T2DM using a 3-state mode²⁷ (144). This model is simplified in comparison; however, the main conclusion is that that after diagnosis most time is spent with HbA1c above 6.4% which is less informative for impactibility to translate into action.

The transition matrices have been defined so that observed movements from State 1 to 3 must transition via State 2. Setting illogical instantaneous transitions to zero is not always adopted (144) but is a strength as the model solves for rates more closely representing the underlying process.

An equivalent force of mortality to the model data would be approximately 0.002 based on the Scottish population (129). In comparison, the transition rates in the final column of Table 16 and Table 17, appear low. This discrepancy is seen in the inaccuracy in Figure 26 and Figure 27. The lack of credible data for transitions to deceased warrants using a transition intensity offsets based on a relevant population or T2DM mortality table (145).

This would improve the fit for the BMI model over time; by absorbing lives in the deceased state the overestimates in others would be reduced at longer time periods. A similar

²⁷ The 3 states are defined as: HbA1c $\leq 5.6\%$ as Normal, $\leq 6.4\%$ as Pre-diabetic and $> 6.4\%$ as Diabetic

improvement would occur for the HbA1c model however, it would not correct its inaccuracy at earlier time periods.

8.2.2.2 Cohort

The cohort is defined to remove the impact of confounders however, it is clear from the results of the HbA1c model that the assumption regarding duration is not fit for purpose. The inaccuracy seen in the Excellent and Very poor HbA1c states suggests a durational affect is present in the process. The dataset has more observations in year 1 of diagnosis than any other and as such transition rates are influenced by shorter durations which do not appear to be indicative of later durations. A duration-based variable is required in the model design.

8.2.2.3 Explanatory variable test

Having only two IMD groups to compare the most to the least deprived IMD deciles may bias the result toward the null. An improved test may compare the least deprived 30% to the most deprived 30% of IMD scores. However, a reduced amount of data in each sub-group may widen confidence intervals for the odds ratio.

8.3 Implications

This research has implications for future research and for stakeholders in the health and social care system and wider health system.

8.3.1 Future research

There is much that can be done to improve this proof of concept including: use of mortality rate offset, introducing duration, and validating or developing beyond the simplifying assumption²⁸.

A next step is to compare transition rates for those who complete the T2DM education programme, Desmond, to those who did not (146)²⁹. This will illustrate the usefulness of MSM for intervention effectiveness evaluate.

This dissertation furthers the areas of clarity and awareness but has not extended collaboration or preparedness. A summary of a self and group-reflective exercise, which expands on collaboration and awareness, designed and piloted during this project is

²⁸ The proof of concept simplifying assumptions were described in Chapter 6 and are summarised in Appendix 10.

²⁹ Data access for research purposes has been agreed with Imperial College Health Partners for this purpose.

provided in Appendix 12. An evaluation plan is still required and an agreement on an ethical framework³⁰.

8.3.2 Clinical practice, public health policy and practice

PHM requires a closer collaboration between clinical and public health practice to develop agile solutions to the dynamic problem of optimising health under constraints across the wider health system. Two aspects will be relevant immediately; culture and data.

The culture of working in an LHS will need to be established to gain the collaboration that is key to PHM's success as an agile solution (27, 60). This collaboration is developing in the UK however, to be successful a clear link between IM and the common strategic objectives must be established (27); to optimising health under constraints. The ethos of IM could be used when facilitating communications between various stakeholders about the objectives of IM.

Leveraging data insights is crucial to PHM and an LHS (27, 60, 76). To create an agile solution, IM must live within an LHS which "require[s] greater alignment between the analysis and decisions taken; between analysts and the people interested in data quality improvement; and between the analysis and public attitudes regarding appropriate use of data"(80). The first step at the local level may be to ensure data infrastructure, knowledge, and quality are adequate (27, 57, 60, 80). Equally important is managing public expectations regarding the use of anonymised data to improve population health (57, 60, 80). The use of health data is a politically sensitive topic and it is therefore crucial to establish the objectives of IM; to optimise health under constraints.

³⁰ An ethical framework is under development by the working party and academics.

Chapter 9 Conclusion

The sustainability pressures faced by the health systems today will not be the same in the future. To ensure the long-term viability of Universal Health Care provision, agile solutions are being designed to navigate the dynamic problem of optimising health under constraints. IM is a new development in PHM which seeks the greatest increase in population health, patient experience, and reduction in health inequalities for the cost incurred.

It is important to develop and apply IM as an agile solution, so that it may be successful in accommodating the changing nature of the optimisation problem. This dissertation has provided insights in that direction at this early stage of IM development.

There is a cautious yet optimistic view in the literature of IM's ability to achieve the PHM aims and navigate health system sustainability. Practical recommendations for IM's development and application have been distilled into an ethos of IM; awareness, clarity, collaboration, preparedness and working across a wider health system. A proof of concept has shown how recommendations can be applied in practice and makes a case for MSM as useful for IM.

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Appendix 1. University of Edinburgh ethics form

The level 1 ethics form is provided below.

University of Edinburgh,
Usher Institute of Population Health Sciences and Informatics
USHER RESEARCH ETHICS GROUP

Self-Audit Checklist for Level 1 Ethical Review for Taught Masters and UG dissertation projects

NOTE to student: Completion of this form should be under the oversight of your supervisor. A good strategy would be to complete a draft as best you can, then discuss with your supervisor before completing a final copy for your supervisor to sign (Relevant information is available on Learn VLE.)

Proposed Project (State research question and topic area, and briefly describe method/ data. Specify also countries in which data will be collected.):

In parallel with membership on the IFoA and NHS joint Population Health management working party, undertaking a Masters in Public Health dissertation on impactability modelling using type II diabetes as a worked example. Analysis will be quantitative based on secondary UK likely linked care data. The initial plan is to assess transitions through states of type II diabetes including pre-diabetic, new and established diabetic and respective cost profiles of well managed or less so. An area of initial interest would be to assess the pace of transition by risk strata and the profile of those with a high cost profile compared to others in the same state. Therefore, can a risk profile of those who are impactable be created; potential to regress through diabetic states and potential to impact via early preventative intervention for those less able to regress. This type of impactability modelling could be helpful in attributing research to health needs assessments, efficacy of treatment and potential preventative measures such as targeted social prescribing.

Data access is currently being negotiated and may be on WSIC or a Scottish equivalent. The Whole Systems Integrated Care (WSIC) dataset is of North West London and would involve working in house with Andi Orlowski at Imperial College Health Partners, a fellow member of the working party and researcher in impactability modelling. Access to the Scottish equivalent is currently being investigated with Sarah Wild.

1. Bringing the University into disrepute
Is there any aspect of the proposed research which might bring the University into disrepute? YES/ NO

2. Data protection and consent
Are there any issues of DATA PROTECTION or CONSENT which are NOT adequately dealt with via established procedures? YES/ NO

These include well-established sets of undertakings. For example, a 'No' answer is justified *only if*:

(a) There is compliance with the University of Edinburgh's Data Protection procedures (see www.recordsmanagement.ed.ac.uk);

(b) Respondents give consent regarding the collection, storage and, if appropriate, archiving and destruction of data;

(c) Identifying information (eg consent forms) is held separately from data;

(d) There is Caldicott Guardian approval for (or approval will be obtained prior to) obtaining/ analysing NHS patient-data.

(e) There are no other special issues arising about confidentiality/consent.

3. Study participants
a) Will a study researcher be in direct contact with participants to collect data, whether face-to-face, or by telephone, electronic means or post, or by observation? (eg interviews, focus groups, questionnaires, assessments) YES/ NO

b) Answer this *only if* qu. 3 above = 'YES':
In ethical terms, could any participants in the research be considered to be 'vulnerable'?
e.g. children & young people under age of 16, people who are in custody or care (incl. school), a marginalised/stigmatised group

Please tick one:
'vulnerable' ☐ not 'vulnerable' ☐

4. Moral issues and Researcher/Institutional Conflicts of Interest
Are there any SPECIAL MORAL ISSUES/CONFLICTS OF INTEREST? YES/ NO

(a) An example of conflict of interest for a researcher would be a financial or non-financial benefit for him/herself or for a relative of friend.

- (b) Particular moral issues or concerns could arise, for example where the purposes of research are concealed, where respondents are unable to provide informed consent, or where research findings could impinge negatively/ differentially upon the interests of participants.
- (c) Where there is a dual relationship between researcher and participant (eg where research is undertaken by practitioners so that the participant might be unclear as to the distinction between 'care' and research)

5. Protection of research subject confidentiality

Are there any issues of **CONFIDENTIALITY** which are **NOT** adequately handled by normal tenets of confidentiality for academic research?

YES/ NO

These include well-established sets of undertakings that should be agreed with collaborating and participating individuals/organisations. For example, a 'No' answer is justified only if:

- (a) There will be no attribution of individual responses;
- (b) Individuals (and, where appropriate, organisations) are anonymised in stored data, publications and presentation;
- (c) There has been specific agreement with respondents regarding feedback to collaborators and publication.

6. Potential physical or psychological harm, discomfort or stress

- (a) Is there a **FORSEEABLE POTENTIAL** for **PSYCHOLOGICAL HARM** or **STRESS** for participants?

YES/ NO

- (b) Is there a **FORSEEABLE POTENTIAL** for **PHYSICAL HARM** or **DISCOMFORT** for participants?

YES/ NO

- (c) Is there a **FORSEEABLE RISK** to the researcher?

YES/ NO

Examples of issues/ topics that have the potential to cause psychological harm, discomfort or distress and should lead you to answer 'yes' to this question include, but are not limited to: relationship breakdown; bullying; bereavement; mental health difficulties; trauma / PTSD; violence or sexual violence; physical, sexual or emotional abuse in either children or adults.

7. Duty to disseminate research findings

Are there issues which will prevent all relevant stakeholders* having access to a clear, understandable and accurate summary of the research findings if they wish?

YES/ NO

* If, and only if, you answered 'yes' to 3 above, 'stakeholders' includes the participants in the research

Overall assessment

- If every answer above is a definite NO, the self-audit has been conducted and confirms the **ABSENCE OF REASONABLY FORESEEABLE ETHICAL RISKS** – please tick box ☒ This means that regarding this study, as currently self-audited, no further ethical review actions are required within Usher. However, if in the coming weeks/months there is any change to the research plan envisaged now (and outlined above), the study should be **re-audited** against a Level 1 form, because it may be that the change made negates the absence of ethical risks signed off here.
- If one or more answers are YES, then risks have been identified and prior to commencing any data collection **formal ethical review is required** - either:
- ~ by NHS REC (NB copy of ethics application and decision letter to be sent to CPHS Ethics); or
 - ~ if not to be formally reviewed by NHS REC, then Usher **level 2/3 ethical review required**. [If either 4 is 'yes' or 3b is 'vulnerable' then it is possible level 3 review is required.]

Student Exam Number: 6654040

Please see next sheet for names and signatures

Note regarding version of level 1 form bound into MPH dissertation:

The signed hard copy of this Level 1 form has been lodged with the Usher Research Degree committee. In accordance with usual Level 1 self-audit process, the form was completed and signed by the masters/UG student, with oversight by his/her Supervisor, who countersigned to confirm this.

However, in order to preserve anonymity of students through the marking process, student and supervisor names and signatures (the additional sheet) have been excluded from the dissertation submitted for marking.

The overall assessment shown above is identical with that shown on the signed-off form lodged.

Signed:

Shant Malla

Postgraduate administrator

Appendix 2. The PHM Working Party

Further details on the Institute and Faculty of Actuaries PHM working party can be found in the link below.

<https://www.actuaries.org.uk/practice-areas/health-and-care/research-working-parties/population-health-management>

Working members names, positions, and institutions are listed below.

Table 26: Population Health Management Working Party membership

Names	Position	Institution
Alpesh Shah	Actuary, Chair	PwC
David Beddows	Actuary, Deputy Chair	Optum Health Solutions
Chris Bull	Actuary	Government Actuary's Department
Dr Illyas Bakbergenuly	Actuary	University of East Anglia
Mark Flint	Actuary	SCOR
B6654040	Actuary	University of Edinburgh
Mei Sum Chan	Actuary	University of Oxford
Craig Swatton	Actuary	Swiss Re
John Seymour	Actuary	PwC
James Umpleby	Senior Analytical Manager	NHS England
Tanya Hayward	Actuary	Milliman
Joanna Buckle	Actuary	Milliman
Dr Sarah Culkin	Data policy	NHS England
Mohamed Elsheemy	Actuary	NHS England
Stephen Lorrimer	Head of Analysis & Insight	NHS England
Dr Chris Martin	Head of Modelling	Crystallise
Dr Thomas Mason	-	NHS England
Adam Millican-Slater	Palliative Care Development Manager	NHS England
Lisa Morgan	Actuary	International Labour Organisation, WHO
Dr Carlos Jackson	Chief Data & Analytics Officer	Community Care of North Carolina
Andi Orlowski	Health Economist	Imperial College Health Partners

Appendix 3. Creating a distinction in the IM proposals


There is a distinction within the proposals in Table 2, Section 4.2.2.2, that is not clearly established in the literature. Data analytics can be leveraged in a PHM system to highlight unwarranted variation in service provision and utilisation (10). Proposal 4 involves opportunity analysis to improve quality by finding duplication or gaps in care (10, 22, 25).

Analysis of data that highlights lives currently not receiving the required interventions, i.e. under-provision, or receiving more intervention than necessary, i.e. over provision, would result in action to navigate towards adequate and appropriate provision. These actions thereby improve the timely and equitable delivery of care (25). Optimising health within the health and social care system, using these IoM's quality of care dimensions (12), is a sub-component of the wider health system PHM aims, as discussed in Chapter 2. Closing gaps in care works toward the PHM aims (28) but not, as argued here, for the objective of IM. This is because understanding why lives are not provided with required interventions provides reflection on the quality in the delivery of services, not a reflection on the impact created by the delivery of quality services.

This distinction is emphasised when considering the resulting action when services are not delivered to high quality vs the action taken when the delivery of quality services does not create an impact. Poor quality delivery of care in primary and community settings is considered to increase care in hospitals for Ambulatory Care Sensitive Condition ('ACSC') (22, 25). Actions to improve the delivery of care include Audit and Feedback practices where regular monitoring seeks closer adherence to intervention guidelines i.e. the delivery of required interventions (147, 148). Financial incentives based on audit outcomes are used to incentivise the continuous improvement in provision, to navigate toward an appropriate and adequate provision of care. For example, diabetes is an ACSC and financial remuneration under Quality and Outcomes Framework ('QOF') is used to improve the provision of care (131).

Table 27 shows that the actions taken when there are service delivery issues result in actions that navigate to an appropriate and adequate provision. At this stage, impactibility can be assessed. Under proposal 4, gap analysis variation in utilisation and propensity to benefit analysis are suggested.

Table 27: Recommended action by delivery category

Delivery	Action	Navigating
Poor provision <i>Poor quality services are delivered</i>	Improve quality dimensions: safe, effective and patient-centred	
Under provision <i>Good quality services that are under delivered</i>	Improve quality dimensions of timely and equitable	
Appropriate and adequate provision <i>Good quality services that are delivered adequately</i>	Assess impactibility	
Over provision <i>Good quality services that are over delivered</i>	Improve quality dimensions of efficiency	

Closing gaps in care, after a gap analysis, or prioritising gaps in care with a larger variation or health importance, after a weighted gap analysis, are actions undertaken to rectify delivery issues. In addition, analysis to avoid triple fail events³¹ (22) seek to improve the safe, effective and patient-centred dimension of quality care (12, 28). That is, to navigate away from poor-provision to adequate and appropriate provision.

Analysis to understand variability in utilisation such as low-risk lives with high utilisation or high-risk lives with low utilisation are more nuanced. Variability in utilisation may be an indication of intervention delivery issues or an indication of patient preferences (25), as shown in Table 28. An understanding of what drives the variability will guide the resulting action. Where the variation is due to delivery issues, the action would navigate toward adequate and appropriate provision. Where the variation is due to patient preferences, IM would be warranted to understand the risk and impactibility drivers to tailor resources according to patient preferences, discussed in Section 4.2.3.2.

Table 28: Understanding the drivers of utilisation by risk

Risk	Utilisation	
	High	Low
High	Expected	Patient preference
Low		Under provision
	Patient preference	Expected
	Over provision	

Propensity to benefit scores are based on analysis that assesses how far an individual's health status is from those resulting from following care guideline recommendations (71). This model assumes an intervention has a full impact and need only be provided to improve health status. This model does not analyse impactibility but assumes all lives have full scope

³¹ Triple fail events are where care does not improve health, is not patient-centered, and does so at a cost.

to benefit given adequate and appropriate provision. The resulting action is therefore to navigate toward adequate and appropriate provision.

It is argued here, that IM should analyse if an intervention creates an impact where there is appropriate and adequate provision of care. Therefore, although similar to IM, proposals based on service provision or utilisation that result in action to navigate toward adequate and appropriate provision are not progressed in this dissertation. It is argued here that these do not meet the IM objective in the working definition (43).

Focusing on IM proposals that only consider the optimisation problem within the health and social care system instead of the wider health system, would hinder potential of IM to be developed an agile solution adaptive the dynamic nature of the problem. Similarly, proposals where the aims are limited to the 6 dimensions of quality care instead of the PHM aims, works to limit the potential solutions to those of service delivery and utilisation instead of creating structural health system changes in the wider health system to accommodate the dynamic problem.

Appendix 4. Literature search

Alternative terminology

Within health economics the concept of priority-setting and rationing are relevant. Selecting patients with the greatest return on investment ('ROI') is considered under patient selection rationing (45).

Clinical judgement and decision-making are practical elements of medical practice. The topics of triage and case-finding helped contextualise the development of decision-making aids and the ethical considerations of IM (46).

Precision medicine is "an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person" to identify an effective approach (47). Genomics and pharmacogenomics (113) were not considered further as routine population data is not available for analysis. Finding an intervention that is beneficial to a patient's health given their characteristics was considered further.

References by relevance

To increase transparency of the literature search, a list of references by relevance grading is provided in Table 29 and a list of excluded citations.

Table 29: Relevance grading - with references

Second review: Full body text	References
Low – background information 37 sources	(16, 32-34, 44-47, 50, 54, 55, 58, 61-63, 68-70, 77, 81, 83, 84, 88, 89, 94-96, 101-106, 111, 113, 149, 150)
Medium – related to wider context 26 sources	(7, 23, 27, 31, 35, 41, 49, 51, 57, 59, 60, 65, 79, 80, 82, 85-87, 90, 97, 98, 107, 142, 148, 151)
High – directly related to 'impactability' or IM 19 sources	(8, 22, 25, 26, 28, 44, 52, 53, 56, 67, 71-76, 78, 91, 152)

Excluded citations

Citations that were deemed not relevant are shown below for transparency.

ACADEMYHEALTH. 2008. 2008 HSR Impact Awardee: Risk-Based Predictive Modeling - Improving the Financing and Delivery of Health Care with Risk-Based Predictive Modeling [Online]. Washington, USA: Academy Health. Available: <https://www.academyhealth.org/sites/default/files/risk-basedpredictivemodeling.pdf> [Accessed 01 June 2019].

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Appendix 5. Primary research for criteria derivation

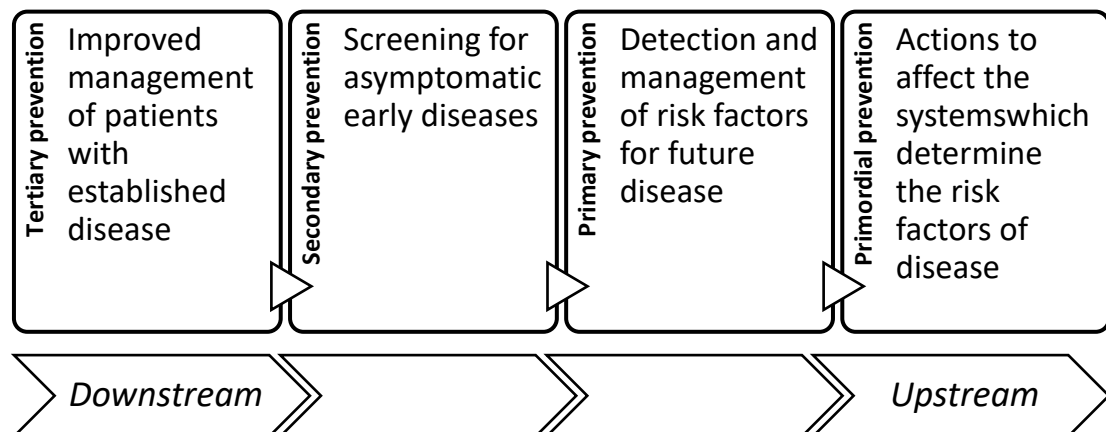
Primary research may be required to derive impactibility criteria to better tailor resources to achieve the PHM aims (44, 79, 82-84).

Data can be collected, quantitatively and qualitatively, and combined from multiple stakeholders across multiple organisations to derive impactibility criteria (151). Data collected directly from patients is seen as crucial to find suitable interventions to tackle the wider determinants of health (79, 82, 149). In addition, data direct from patients is seen as useful where patient behaviour plays a role in managing the outcome of interest (13, 44, 75, 84, 87, 89). This is because understanding the drivers of former non-compliance, disenrollment or unwillingness to participate in an intervention could help tailor the intervention (25, 53). Measures of patient activation or engagement could be tested as explanatory factors for impactibility (25, 85, 86). The actions resulting may be to tailor interventions to first improve patient engagement (25, 75, 79, 84, 88) using behavioural economics (13) or change theory (75, 87) as part of better managing the outcome of interest.

Appendix 6. Possible interventions: stages of prevention

Intervention can be provided at different stages of disease progression to prevent an adverse health outcome. The range of downstream to upstream interventions can be described as four prevention stages (92, 93), shown in Figure 30. References to interventions in the literature are summarised under each stage.

Figure 30: Intervention stages at each level of prevention



Based on *Disease prevention: a critical toolkit* (93)(p.11)

Tertiary prevention

Where a disease has occurred and is symptomatic, interventions can be considered tertiary prevention (92). In the literature, the improved management of patients with established disease is anticipated to achieve the PHM aims (16, 26, 52, 94, 95). In the UK, these include case management, self-management programmes, and altering the location of care delivery (4, 8, 24, 33, 34, 96).

Secondary prevention

Where a disease is detectable but asymptomatic interventions are referred to as secondary prevention (92, 93). Population wide screening is an action which aims to provide interventions earlier to improve health status at a reduced cost i.e. two of the PHM aims. In the UK, this includes national cancer screening programmes and the NHS Health Check, which provides free screening every 5 years from age 40 to 74 for chronic conditions including diabetes (117).

Primary prevention

Although there is always a risk of disease in a population, some are more at-risk than others (92). Primary prevention seeks the detection of risk factors for future disease and the management of modifiable risk factors include diet and physical activity (92, 93). The NHS Health Check provides advice on modifiable risk factor management to reduce disease risk (117).

The literature highlights the need to consider, at an individual level, the contributors to risk and impactability such as housing, transportation, financial stressors, and behavioural aspects including medication adherence, exercise, diet, and substance use and abuse including tobacco, drugs and alcohol (8, 25, 75, 76, 79, 97, 98).

Primordial prevention

At a primordial prevention stage, actions are focussed on the wider health system which enables risk factors for disease to be high or increasing in prevalence in society (92, 93). In the UK, examples include public smoking bans, minimum unit alcohol pricing and sugar sweetened beverage tax.

Stokes et al. stresses the importance of recognising social factors that drive risk and impactability, noting that these are “multifaceted, deeply ingrained and linked to the wider social context, and therefore highly resistant to change” at an individual level (8)(p.249).

Appendix 7. Testing predictive model accuracy

To test predictive model accuracy, measures such as areas under the receiver curve, c-statistic, sensitivity, positive predictive value, r-squared and observed vs. expected analysis are evident in the literature. A summary of these is provided here for ease of reference to IM developers.

The area under the receiver operating characteristics ('ROC') curve is used to portray model accuracy (25) alongside the c-statistic (68). The C-statistic uses the distribution of true positives and true negatives across the model output (24). However, for PM to be beneficial in a PHM system, the benefits of using it must outweigh the costs (24) which usually gives rise to a chosen cut-off for the level of risk or impact deemed worth intervention (24). Where only the accuracy beyond the chosen cut-off is required, measures of sensitivity and positive predictive value are useful (24), as shown in Table 30.

Table 30: Predictive power categorisation

Actual Predicted	+	-	Total	Accuracy Test
+	<i>True positive</i> A	<i>False positive</i> B	A+B	<i>Positive Predictive Value</i> $A/(A+B)$
-	<i>False negative</i> C	<i>True negative</i> D	C+D	<i>Negative Predictive Value</i> $D/(D+C)$
Total	A+C	B+D	A+B+C+D	
Accuracy test	<i>Sensitivity</i> $A/(A+C)$	<i>Specificity</i> $D/(D+B)$		

Based on text from Lewis (24)

The r-squared ('R²') value is an appropriate measure of predictive accuracy at an individual level; representing the "total variation among individual observations that could be explained by the model" (59)(p.157). However, at a grouped level, a predictive ratio like observed vs expected (O/E) is more appropriate (59).

Appendix 8. Working description of MSM theory

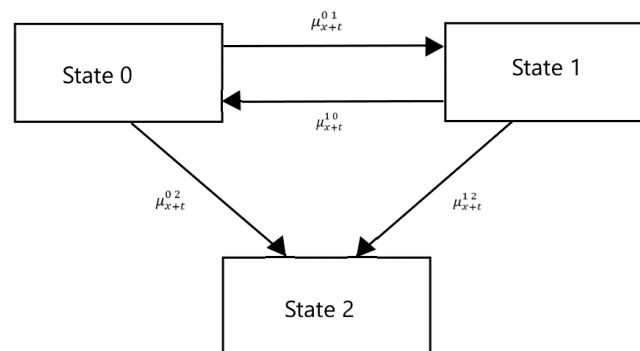
A working description of MSM theory is provided here but full explanation can be found in MSM textbooks (118, 119).

An individual's life history is considered as "represented by time spent in states and movement between states" (119) (p.256). An individual can occupy one of the possible "states" at any given time and moves between states at random times governed by the probabilistic model" (119) (p.xv). Therefore, to specify a mathematical model of the life history, a state space and transition intensities are required (119)(p.257).

State space

The state space describes the collection of states possible for an individual to occupy at any particular time (119)(p.256). Figure 31 shows a MSM with transient states 0 and 1, with a means of exit, and an absorbing state 2, with no possible means of exit (118).

Figure 31: State space example



Adapted from Modelling Mortality with Actuarial Applications textbook (119) (p.258)

It should be possible to determine the state occupied by an individual at a given time. It is the modeller's choice to define meaningful states "that allow the objective of modelling and analysis to be met" (118)(p.2). In practice, the number of states is often reduced for model parsimony. A balance between the number of states, the information available in the data and the credibility of results is also a model choice (143).

In general, there can be $M+1$ states considered for the i^{th} of n individuals in a population. Transitions between these states are counted. For each pair $j \neq k$ of state labels, $\mathcal{N}_i^{jk}(t)$ is defined to be the number of transition from state j to state k made by the i^{th} individual (119)(p.257). A counting process is established based on the observed "number and times of transitions between each pair of sates in the model" (119)(p.xv).

Transition intensity

Transition intensities between states define the model. These are the forces to which an individual is subject; keeping the individual in the current state or transitioning to another state.

In Figure 31, the arrows indicate possible transitions:

- It is possible to transition from state 0 to 1, state 1 to 0, state 0 to 2, state 1 to 2, with the relevant transition intensity at age $x + t$ denoted by μ_{x+t}^{jk}
- It is not possible to transition from state 2 to 0, or state 2 to 1 so no arrows are shown i.e. the transition intensity is set to zero, $\mu_{x+t}^{20} = \mu_{x+t}^{21} = 0$

A transition intensity matrix, shown below, has rows that indicate the state held and columns the potential transition state and contains all transition intensity rates.

Equation 2: Transition intensity matrix

$$Q(t) = \begin{bmatrix} \mu_x^{00} & \mu_x^{01} & \dots & \mu_x^{0M} \\ \mu_x^{10} & \mu_x^{11} & \dots & \mu_x^{1M} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_x^{M0} & \mu_x^{M1} & \dots & \mu_x^{MM} \end{bmatrix}$$

Transitions not allowed in the process between pairs of states should have transition intensities set to zero in the matrix, for example returning from deceased to healthy. Otherwise, transition intensities are inferred from suitable life history data; that is, data containing “transitions between pairs of states at random times” (119)(p.xv). Transition intensities can depend on covariates which act in a multiplicative or additive fashion (118)(p.9).

Transition intensities are defined below and are linked to transition probabilities.

- For $i \neq j$, over a small dt then μ_{x+t}^{ij} is defined to be the transition intensity from state i to state j at age $x + t$, as $\mu_{x+t}^{ij} = \lim_{dt \rightarrow 0} \frac{dt p_{x+t}^{ij}}{dt}$.

Transition probabilities

Transition probabilities follow on from transition intensities as “ $\mathcal{P}(t)$ can be calculated by taking the matrix exponential of the scaled transition intensity matrix” (134)(p.6).

The transition probability matrix, shown below, has rows that indicate the state held and columns the potential transition state.

Equation 3: Transition probability matrix

$$\mathcal{P}_x(t) = \begin{bmatrix} {}_t p_x^{00} & {}_t p_x^{01} & \dots & {}_t p_x^{0M} \\ {}_t p_x^{10} & {}_t p_x^{11} & \dots & {}_t p_x^{1M} \\ \vdots & \vdots & \ddots & \vdots \\ {}_t p_x^{M0} & {}_t p_x^{M1} & \dots & {}_t p_x^{MM} \end{bmatrix}$$

Transition probabilities are defined as:

- ${}_t p_x^{ij}$ is the probability that an individual in state i at age x will be in state j at age $x + t$
- ${}_t p_x^{ii}$ is the probability that an individual in state i at age x will be in state i at age $x + t$, noting that this does not require stationarity in state i
- ${}_t p_x^{\overline{ii}}$ is the probability that an individual in state i at age x will remain in state i until at least age $x + t$ (known as occupancy probability)

Counting Process, Indicator Function and Martingale

Fitting a parametric model to complete life history data has similarities to likelihood in Poisson distribution, $\text{Poi}(\lambda)$. Each event is counted over a period of time where “a transition from one state to another can be considered as a type of event” (118)(p.2).

An indicator function, $Y_j^i(t)$, is used to specify the life history in terms of a counting process used to generate transition intensities, μ_{x+t}^{ij} . The indicator function has martingale properties such that all information prior to time t is included at time, t , in the current state, satisfying the Markov property which simplifies the mathematics (see (118, 119) for further information).

Once the counting process is defined, inference can be made from the observed data.

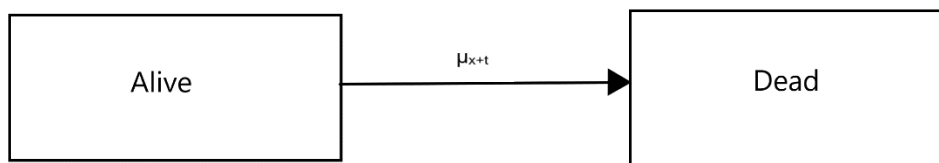
Alive-Dead Model

A familiar example of Poisson counting process can be represented in a MSM model. For a Poisson GLM analysis of mortality rates, μ_x , the model requires the time of exposure to risk of death and the number of deaths in the period, counted as occurring, 1 or not, 0. This count is similar to the indicator used in the MSM model and the time period between observations as the exposure to risk.

Just as Poisson GLM provides an instantaneous force of mortality, the MSM provides an instantaneous transition intensity represented as: μ_{x+t}^{AD}

The transition intensity for a two state, alive-dead, model would provide force of mortality μ_{x+t} for a give age x . Deceased here would be an absorbing state as no life can return from dead to alive. This is represented in the state space in Figure 32 with a one directional arrow to Dead, without a returning arrow.

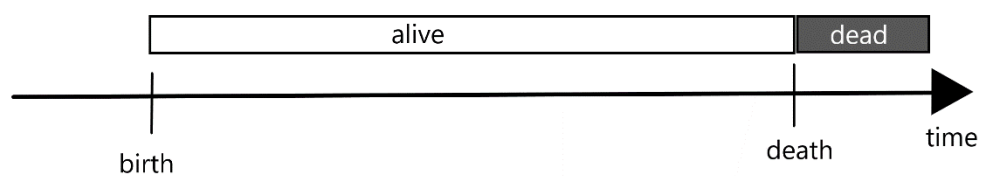
Figure 32: Alive-dead state space



Based on textbook (119)(p.256)

The Alive state, in the timeline shown in Figure 33, can be broken down further into multiple states which gives rise to a multi-state model.

Figure 33: Life event timeline



Appendix 9. MSM data frame example

A data frame is prepared to the *msm* R package input requirements of a counting process format; each row is an event that shows “the time of the observation and the observed state of the process” (134)(p.15).

An example data frame for the model is provided below. Time is accumulative in months. IMD deciles from the data are grouped; group 1 is the most deprived with IMD deciles [1,5] and group 2 is the least deprived with IMD deciles [6,10].

Table 31: Example data frame

Unique ID anonymised	State	Time Months	Explanatory variable IMD group (1 or 2)
i	1	0	1
i	2	2.5	1
i	2	5	1
$i + 1$	1	0	2
$i + 1$	4	4.5	2
\vdots	\vdots	\vdots	\vdots
\vdots	\vdots	\vdots	\vdots
n	1	0	1
n	2	1	1
n	6	5	1

Appendix 10. Summary of simplifying assumptions

Simplification made, in the spirit of a proof of concept and for model parsimony, are summarised in Table 32. These would need validation before developing the model beyond a proof of concept.

Table 32: Summary of simplifying assumptions

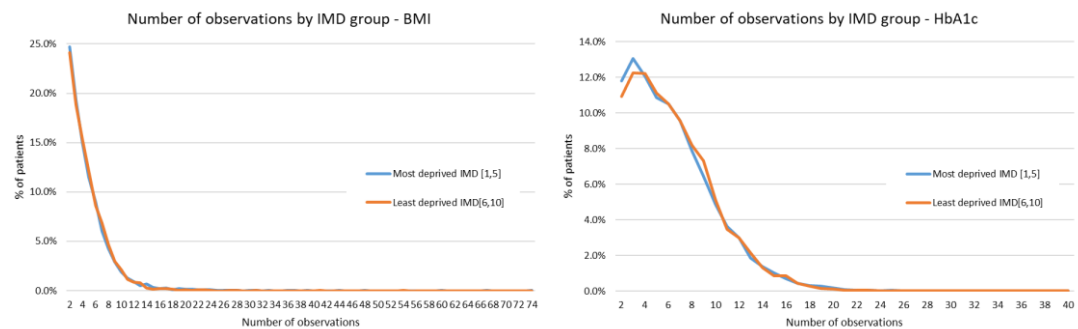
Area	Assumption
Age	Assumed to be no material change in transition rates in 10-year age range
Morbidities	Low prevalence in age at diagnosis [40,49] No material variation between IMD groups.
Duration	Assumed to be no material change in transition rates in 5-year period after diagnosis
Intervention	A range of guideline interventions used in the first 5 years of diagnosis can be analysed under 'current practice'. No material variation in intervention use between IMD groups.
Selection bias	Assumed to be limited There is considered to be no bias in the lives missing HbA1c or BMI from there medical records. Those with one event in a 5-year period are not assumed to be inherently different to all lives.
Follow up bias	Assumed to be limited No material forms of exit other than death
Missing data	The provision of private health care for chronic disease is considered not to be material. The removal of data with missing postcodes is not considered to introduce bias.
Confounders	The variation by IMD group for gender, age, duration and morbidity are not material. Smoking does not impact BMI or HbA1c control.

Appendix 11. Additional results

Number of observations

Figure 34 shows the similar distribution of observations by IMD group in the full dataset for both models.

Figure 34: Distribution of patients by count of observations and IMD group



Data summary - BMI

From the BMI training dataset the movements of the most and least deprived IMD groups are provided in Table 33 and Table 34.

Table 33: BMI observed transitions - most deprived IMD group

State	To					
From	Under/ Normal	Pre- obesity	Obesity 1	Obesity 2	Obesity 3	Deceased
Under/Normal	1148	101	1	0	0	18
Pre-obesity	122	3038	298	1	0	23
Obesity 1	1	375	4944	328	1	21
Obesity 2	1	1	455	4224	254	17
Obesity 3	0	0	7	358	4932	20
Deceased	0	0	0	0	0	0

Table 34: BMI observed transitions - least deprived IMD group

State	To					
From	Under/ Normal	Pre- obesity	Obesity 1	Obesity 2	Obesity 3	Deceased
Under/Normal	852	86	1	0	0	7
Pre-obesity	103	1893	212	0	0	12
Obesity 1	1	239	3052	189	0	10
Obesity 2	0	1	245	2090	149	6
Obesity 3	0	0	1	202	2327	9
Deceased	0	0	0	0	0	0

Data summary – HbA1c

From the HbA1c training dataset the movements of the most and least deprived IMD groups are provided in Table 35 and Table 36.

Table 35: HbA1c observed transitions - most deprived IMD group

State	To					
From	Excellent	Good	Poor	Less than poor	Very poor	Deceased
Excellent	6,694	1,390	409	324	259	28
Good	1,395	1,958	919	752	497	10
Poor	459	794	878	866	561	11
Less than poor	519	813	938	1,953	1,359	12
Very poor	510	594	627	1,821	6,646	39
Deceased	-	-	-	-	-	-

Table 36: HbA1c observed transitions - least deprived IMD group

State	To					
From	Excellent	Good	Poor	Less than poor	Very poor	Deceased
Excellent	3,886	842	244	169	115	19
Good	838	1,303	537	465	265	10
Poor	256	514	555	523	270	1
Less than poor	242	495	533	1,213	832	7
Very poor	284	341	342	1,084	3,477	11
Deceased	-	-	-	-	-	-

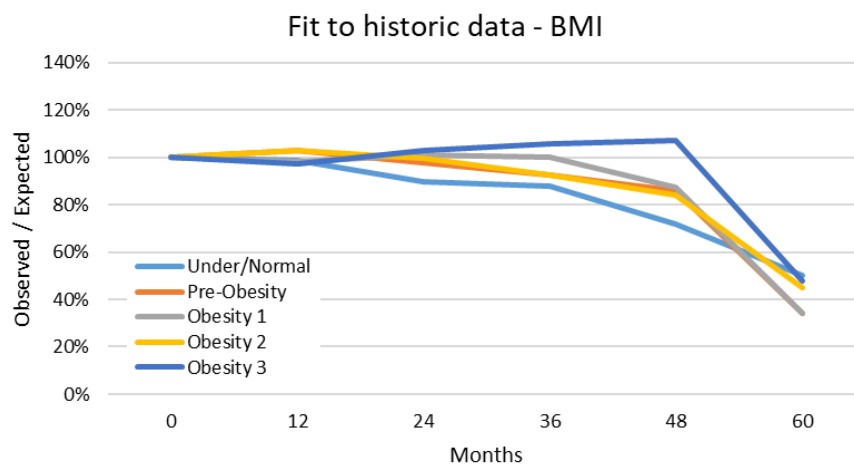
Fit to historic data

The impact of inaccuracies in the transition rates accumulates over a longer time period causing the model fit to deteriorate with time as can be seen for both historic data fit for BMI and HbA1c.

BMI

A ratio comparison of observed to expected occupancy in each state is shown in Figure 35. The model fit deteriorates with time. The fit is poorest for Under/Normal which has a lower amount of data and so poorer accuracy in the fit to historic data.

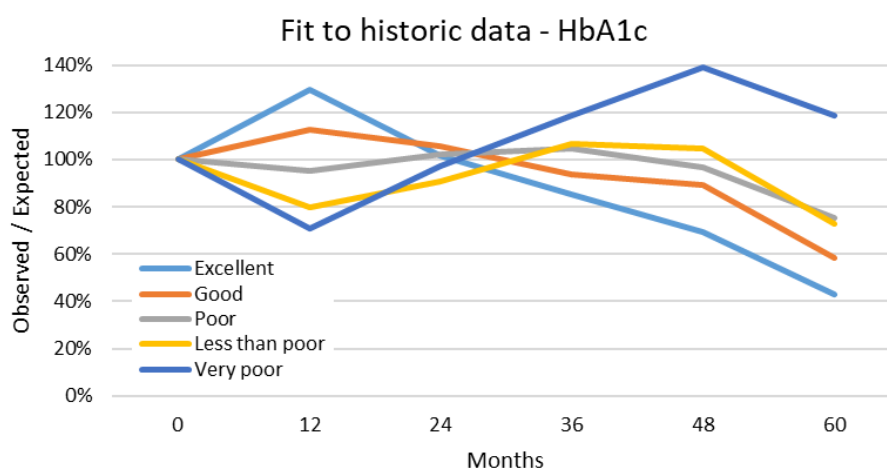
Figure 35: BMI model O/E ratio - historic data



HbA1c

The inaccuracy of the model for the short-lived affect within year 1 for Excellent and Very poor is clear, in Figure 36.

Figure 36: HbA1c model O/E ratio - historic data



Appendix 12. A collaboration and awareness exercise

Collaboration and awareness are an important element of IM. As a first step, in this direction I created an exercise to capture my own values and beliefs in a self-reflective exercise. An opportunity arose to pilot this within a group setting and the process developed is shared here and in the working party's first output (43)³²

When building, choosing, parameterising and using a model there are many choices faced by the user. The decision-making process is informed by prior experiences, values and beliefs. These elements can either be consciously or unconsciously embedded into a model. I thought it was important to take time to reflect on the nature of my views and how they may differ from others. A means was sought to bring awareness to prior experiences, values and belief that frame my actions and decisions. The consequences desired and undesired of impactibility, and of wider population health management, were considered in a self-reflective exercise. An opportunity to pilot this as a group exercise was presented by the working party which enhanced my understanding and expand my consideration further.

Reflexivity is “the conscious examination of past experiences, thoughts and ways of doing things”(153). I considered this an important element of model development in a health context as it “challenges the status quo of practice, thoughts and assumptions”(153).

Neneh Rowa-Dewar, a qualitative researcher at the University of Edinburgh, was consulted on if previous examples or a framework was available for this exercise. Neneh kindly directed me to the University of Edinburgh's online Reflection Toolkit (153). After reviewing different methods, an initial attempt at a self- and group-reflection exercise was piloted with the Working Party. An example of the exercise and practical guidance is shared here so others developing IM may consider a process like this, for the benefit of collaboration and awareness.

This process seeks to:

- “Increase/improve performance and skills;
- Increase awareness of ability and attribute and provide evidence for these;
- Evaluate the quality and success of action plans; and,
- Apply theoretical knowledge/frameworks to real experiences to expand understanding of underlying theory” (153)

This was considered important to evidence:

- conscious consideration for professionalism;
- conscious consideration for multiple stakeholder views;
- responsible and ethical use of modelling in a health context;
- reflection on awareness and availability of ethics support; and,
- ethical consideration for public health issues including health inequalities.

The following learnings resulted from the group pilot:

³² The output is not yet published. This work was undertaken by the author alone and the process was piloted in the working party group setting.

- Sufficient time should be allowed for self (min 1.5 hours) and group (min 2.5 hours) reflection as allowing discussions time to unfold creates fruitful learning opportunities;
- A format should be provided where all in the group feel comfortable contributing to discussions with consideration for group size and independent/experienced facilitators
- A wide range of valid views highlighted the complexity within health modelling and the need for clarity and transparency;
- A structured process was helpful in navigating reflection within a group environment.

Summary

The following are shared with IM developers as areas that were considered essential and recommended in this exercise.

Essential to do:

- create time early in on in project management of model development to discuss reflection, the appetite to undertake reflection and agree a framework to undertaken reflection
- discuss how reflection may benefit the outcome of the project, create a plan and allocate time accordingly

Recommendation

- pilot a self-reflection exercise ensuring that actions and improvement are the key outcome
- pilot a group reflection exercise with a facilitator, record a summary of discussions and actions and improvements
- create a plan of how actions and improvement will be further embedded into work

Template Reflexive Exercise Process

A template reflexive exercise is shared based on the work undertaken. Steps in the process may involve:

1. Complete a self-reflexive exercise an example structure is provide below. The exercise may take 1 hour to complete, with individuals encouraged to write answers down to encourage self-reflection. Answers are not shared or seen by anyone other than the individual. Being open, honest and transparent when answering is beneficial. There are no right or wrong answers. The exercise is designed to provoke thought, i.e. reflection. Times were allocated next to each question as a guide for the participant, but it is up to the individual how much time to spend considering each question.
2. Following 1, a group discussion was held. This is an opportunity to discuss the exercise and the experience as a group. Group-reflection was undertaken to increase the working knowledge in the group and to gain an appreciation and learn from others reflection experiences. It is important to establish with the group that not knowing or having answer to the self-reflection questions in 1 is ok; the learning is taken from the process of reflecting on the questions.
3. Follow the group exercise, major themes from the discussion can be circulated to the group. Areas not captured in the group discussion that members believe important can be facilitated through an anonymous survey platform. Actions, agreed within the group, that resulted from the discussion should be created to increase and

improve understanding and awareness. These actions could be set at an individual, sub-group, or group level in a modelling or a separate project team.

Self-reflexive Exercise

Questions for the self-reflexive exercises were drafted. The nature of the items will depend on the nature of the work and the group. Sample questions have been provided but the user can create alternative prompts for reflection.

1. Background

- a. The demographic profile of the group was reflected upon using an anonymous survey. This helped to understand the composition of the group better. Primary data collection requires due consideration of GDPR.
- b. An ethics resource survey was created to understand how comfortable members of the group were with making ethics-based decisions and if support resources were available to the group.

2. Health

- a. Questions regarding health were posed to individuals to consider and for the group to reflect on.
- b. Some example questions include:

- How would you define health?
- What is a strength of the WHO definition for health(1)? What is a weakness? How does your definition compare?
- What does a holistic view of health mean to you?
- What are some determinants of health? For you, your family, you colleagues and patients?

3. Impactability

- a. Questions regarding impactability were posed to individuals to consider and for the group to reflect on.
- b. Some example questions include:

- What does an impact to your health look like to you?
- What does '*creating an impact to health*' mean to you as a professional?
- What does '*impacting the populations' health*' look like?
- What do you believe currently creates an impact on population health? Positively and negatively?

4. Ethic scenarios

- a. Three discussion scenarios were generated for individuals to consider and for the group to reflect on.
- b. One of the example scenarios is provided below:

Smoking has been banned in public places as second-hand smoke is detrimental to health. Taxes are imposed on tobacco with the aim of reducing consumption. Similarly, taxes are imposed on alcohol to reduce consumption.

- How is Minimum Unit Pricing of alcohol similar or different to tobacco?
- Reflecting on tobacco and alcohol, how does the Sugar Sweetened Beverage tax impact health inequalities?
- Reflecting on health interventions at a population level, does mandatory child vaccination raise ethical issues?

5. Stakeholders and perspectives

- a. Individuals were asked to consider different stakeholders and perspectives during the exercise.

Group-reflexive Exercise

A facilitator may be required for the group exercise. This could be a member of the group or an independent person with qualitative research experience such as focus groups.

This is stage sought to establish actions resulting from the reflective exercises.

1. Ground rules were established for group exercise:
 - a. There are no right or wrong answers. Full respect for peer input, values and comments. Never feel forced to share anything you are uncomfortable with and please be respectful of others' boundaries when sharing. No comments will be attributed to any person and to support open discussions Chatham House Rules are in effect.
 - b. "It's only reflection if it strives toward a better understanding"(153). The questions posed to the group are to help reflection on why others may have different perspectives of the same experience of the self-reflective exercise.
 - c. The objective is to find purposeful examination of thoughts and practice
2. Group reflection on background
 - a. Questions were posed to the group regarding the outcome of the background section. These included reflection and action orientated prompts.

Reflection prompts:

- What is your reflection on...?
- Do we perceive an issue with...?

Action orientated prompts:

- What action result from this group discussion?

3. Group reflection on health section and the impactability section in turn
 - a. Questions were posed to the group regarding the outcome of the background section. These included reflection and action orientated prompts.

Reflection prompts:

- What were some of the thoughts that you had that surprised you in this section?
- Were the questions easy to answer? If so, why? If not, why?
- Did you rely on personal or professional experiences to form your answers?

Action orientated prompts:

- How would we ensure that multiple stakeholders views and perspectives are considered in our work?
- How would we as a group ensure we have a rounded view of ...? Encompassing all the elements discussed?
- What action results from this group discussion?
- How would we as a group expand our understanding further?
- What would a good outcome of the work look like to you?

4. Group discussions were had on ethics scenarios
 - a. Questions were posed to the group regarding the outcome of the background section. These included reflection and action orientated prompts.

Reflection prompts:

- Did you feel there were issues in the scenario?
- Do you think the ethical issue could be navigated? How?
- What would improve the situation? What would make the situation worse?
- Why is it ok to...? Why is it not ok to...?

Action orientated prompts:

- How would we ensure that ethics is considered within our work?
- How will we ensure that health inequalities are considered within our work?

5. Actions
 - a. During the pilot, group members were posed questions on how their reflections from 1-5 would be featured in their work
 - b. A member of the group should be made available provide support or facilitate these actions where necessary.